# Exploring Flexible Strategies in Engineering Systems Using Screening Models

## *Applications to Offshore Petroleum Projects*



by

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**ABSTRACT**

Engineering Systems, such as offshore petroleum exploration and production systems, generally require a significant amount of capital investment under various technical and market uncertainties. Choosing appropriate designs and field development strategies is a very challenging task for decision makers because they need to integrate information from multiple disciplines to make decisions while the various uncertainties are still evolving. Traditional engineering practice often focuses on finding "the optimal" solution under deterministic assumptions very early in the conceptual study phase, which leaves a large amount of opportunity unexploited, particularly the value of flexible strategies.

This thesis proposes a new approach to tackle this issue – exploring flexible strategies using mid-fidelity screening models. The screening models interconnect and model physical systems, project development, and economics quantitatively at the mid-fidelity level, which allows decision-makers to explore different strategies with significantly less computational effort compared to high fidelity models. The screening models are at a level of detail that gives reliable rank orders of different strategies under realistic assumptions. Flexibilities are identified and classified at strategic, tactical, and operational levels over a system's lifecycle. Intelligent decision rules will then exercise flexible strategies as uncertainties unfold. This approach can be applied as a "front-end" strategic tool to conduct virtual experiments. This helps identify good strategies from a large number of possibilities and then discipline-based tools can be used for detailed engineering design and economics evaluation.

The present study implemented the use of such screening models for petroleum exploration and production projects. Through two simulation case studies, this thesis illustrates that flexible strategies can significantly improve a project's Expected Net Present Value (ENPV), mitigate downside risks, and capture upside opportunities. As shown in the flexible tieback oilfield development case study, the simulations predicted a 82% improvement of ENPV by enabling architectural and operational flexibility. The distributions of outcomes for different strategies are shown in terms of Value-at-Risk-Gain curves. This thesis develops and demonstrates a generic four-step process and a simulation framework for screening flexible strategies with multi-domain uncertainty for capital-intensive engineering systems.

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# Nomenclature

**Acronyms:**

| | |
|---|---|
| *ARM* | Active Reservoir Management |
| *BCF* | Billon Cubic Feet |
| *CAPEX* | Capital Expenditures [$] |
| *EFA* | Expected Facility Availability [0, 1] |
| *ENPV* | Expected Net Present Value [$] |
| *EOS* | Economy of Scale |
| *FA* | Facility Availability [0, 1] |
| *GRV* | Gross Rock Volume [standard barrel] |
| *MBD* | Thousand Barrels per Day |
| *MMBBL* | Million barrels |
| *MMSCFD* | Million Standard Cubic Feet per Day |
| *NCF* | Net Cash Flow |
| *NPV* | Net Present Value [$] |
| *N/G*: | Net to Gross Ratio |
| *OPEX* | Operating Expenditures [$] |
| *PV* | Pore Volume in reservoir [barrel] |
| *PVT* | Pressure Volume Temperature for hydrocarbons |
| *RB* | Reservoir Barrels under reservoir conditions |
| *RF* | Recovery Factor |
| *SCF* | Standard Cubic Feet |
| *SURF* | Subsea, Umbilicals, Risers, and Flowlines |
| *STB* | Standard Barrels |
| *STOOIP* | Stock Tank Original Oil in Place [standard barrel] |
| *UR* | Ultimate Recovery |
| *VOF* | Value of Flexibility |

**Symbols:**

$A, B$ fixed and variable OPEX parameters

$b_0^{plat}$, $b_1^{plat}$, $a^{plat}$ platform cost parameters for modified *EOS* formula (default $a^{plat} = 0.6$)

$B_o$ oil formation volume factor, [RB/STB], 1.1~1.2

$B_w$ water formation volume factor, [RB/STB], 1.0~1.1

$B_g$ gas formation volume factor, [RB/SCF], 0.0005~0.002

$B_t$ two-phase (liquids with saturated gas) formation volume factor [RB/STB]

$B_{ti}$ initial two-phase formation volume factor [RB/STB]

$B_{gi}$ initial gas formation volume factor [RB/SCF]

$B_{Iw}$ formation volume factor for injected water [RB/STB]

$B_{Ig}$ formation volume factor for injected gas [RB/SCF]

$C_o$ compressibility for oil [psi$^{-1}$], $10 \cdot 10^{-6} \sim 20 \cdot 10^{-6}$

$C_w$ compressibility for water [psi$^{-1}$], $3 \cdot 10^{-6} \sim 5 \cdot 10^{-6}$

$C_g$ compressibility for gas [psi$^{-1}$], $500 \cdot 10^{-6} \sim 1500 \cdot 10^{-6}$

$C_f$ formation compressibility [psi$^{-1}$], $3 \cdot 10^{-6} \sim 8 \cdot 10^{-6}$

$C_{plat}$, $C_{well}$, $C_{surf}$, $C_{export}$, $C_{expand}$

capital expenditures for platform, wells, SURF, export systems, and capacity expansion [$]

$C_{subsea}$, $C_{umbilical}$, $C_{riser}$, $C_{flowline}$

capital expenditures for Subsea, Umbilicals, Risers, and Flowlines (SURF cost)

$C_k\left(\hat{\hat{V}}(t)\right)$ condition for action branch *k*, where *k* = *1~ m*

$dV$ net underground withdrawal of fluids from a reservoir [barrel]

$D_{prod}(t)$, $D_{water\_inj}(t)$, $D_{gas\_inj}(t)$:

number of producers (production wells), water injectors, and gas injectors at time t

***D***(t) reserve distribution vector at time t, it includes elements of $\mu(t)$, $\sigma(t)$, and $\lambda(t)$

$fC_{well\_prod}$, $fC_{well\_water\_inj}$, $fC_{well\_gas\_inj}$

average well cost for producer, water injector, and gas injector

$G$ initial gas in place [BCF]

$G_I$ cumulative gas injection [MMSCF]

$I$(t) new information at time t, such as new estimate of reserves

$m$ number of action branches at each time step

$n_a$ starting year for enabling the exercising of flexibility

$n_b$ ` the last year for enabling the exercising of flexibility

$N$ stock tank original oil in place (STOOIP) [STB]

$N_p$ produced volume of oil [STB]

$NCF(t)$ net cash flow at time t

$p_f$ probability for significant events (such as hurricanes) for shutting down production

$p_r(t)$ probability for discrete change at time t

$P(t)$ crude oil price at time t [$]

$q_o(t)$, $q_g(t)$, $q_w(t)$:

production rates for oil, gas, and water, [MBD], [MMSCFD], [MBD]

$q_{w\_inj}(t)$, $q_{g\_inj}(t)$, $q_{aquifer}(t)$:

injection rates for water, gas, and aquifer [MBD], [MMSCFD], [MBD]

$q_{t\_cap}(t)$, $q_{o\_cap}(t)$, $q_{w\_cap}(t)$, $q_{g\_cap}(t)$

platform's production capacity for total fluids, oil , water, and gas

$q_{w\_inj\_cap}(t)$, $q_{g\_inj\_cap}(t)$

Platform's injection capacity for water and gas

$r$ discount rate

$S_o$ oil saturation in the pore space [% of the total pore volume]

$S_w$ water saturation in the pore space [%]

$S_g$ gas saturation in the pore space [%]

$S_{wi}$ initial water saturation [%]

| | |
|---|---|
| $t_{dev}$ | duration of project development period before first oil, [years] |
| $t_{ramp\_up}$ | production ramp up time [years] |
| $t_{\max}$ | a project's lifetime [years] |
| $V_o$ | volume for oil in a reservoir's pore space [barrel] |
| $V_w$ | volume for water in a reservoir's pore space [barrel] |
| $V_g$ | volume for gas in a reservoir's pore space [barrel] |
| $\vec{V}(t)$ | state vector for system at time t, which includes uncertainty state vector $\vec{V}_1(t)$ and the system's architecture state vector $\vec{V}_2(t)$ |
| $\hat{\vec{V}}(t)$ | estimate of the state vector at time t |
| $W_e$ | aquifer (natural water) influx into reservoir [STB] |
| $W_I$ | cumulative water injection [STB] |
| $\boldsymbol{W}$(t) | vector for model (reserve evolution model) parameters, it includes the following entries: $\alpha$, $\beta_r$, $\gamma$, $\Sigma_0$, and $p_r(t)$ |
| $\alpha$ | exponential decline rate for the standard deviation of $log(reserve)$ |
| $\alpha^{ENPV}_{\cos t\_of\_option}(x\%)$ | local sensitivity of ENPV to the cost of real option around the nominal value $x\%$ |
| $\beta_r$ | exponential decline rate for the variation of random walk |
| $\beta_f$ | ramp-up coefficient for facility availability |
| $\gamma$ | exponential decline rate for the probability of disruptive change |
| $\lambda(t)$ | probability that there are no reserves |
| $\mu(t)$ | mean or median (log(P50)) for reserve distribution at time t |
| $\mu_m$ | (market price) mean drift rate per annum [%] |
| $\sigma(t)$ | (reserves) standard deviation of log(P50) |
| $\sigma_m$ | (market price) volatility per annum [%] |
| $\Sigma_0$ | initial standard variability for random walk of log(P50) |
| $\phi$ | porosity in the oil bearing rock [%] |

| | |
|---|---|
| $\mathit{\Phi}$ | empty set |
| $\Phi(t)$ | tieback option set at time t |
| $\Psi$ | decision rule set |
| $\Delta p_t$ | reservoir pressure drop at one discrete time interval [psi] |
| $\Delta t_f$ | discrete time length for facility availability model. default [3 months] |
| $\Delta(t)$ | the difference between the estimate of reserves at time t and the amount of reserve being handled by existing facilities in a project's remaining lifetime. |

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# Chapter 1 Introduction

## 1.1 Motivation

This thesis is motivated by a gap in the academic literature and practice in the development of complex engineering systems. This gap is that complex engineering systems are not usually designed with the consideration of multi-domain uncertainty and flexibility in design during the conceptual design phase. Development planning of complex engineering systems, such as industrial infrastructure, transportation systems, and aerospace systems, is a very challenging task for decision makers and system architects, because these complex systems need to be designed to operate for several decades while the future is highly uncertain.

Traditional engineering design approaches focus on optimizing a system's performance and value given a rather rigid projection of the future. However, the system's technical factors and external environment are likely to change significantly within a system's long lifecycle. As a result, design without considering uncertainty very likely locks a system into a set of rigid configurations which are not easily modified to satisfy future needs. Although some exceptions exist, such as the Boeing B-52, engineering systems with unintended flexibility are very rare. Engineering systems being locked-in to a fixed configuration can cause large financial losses (e.g., communication satellite systems such as Iridium and Globalstar) and adverse social impacts. For example, Iridium and Globalstar pioneered mobile space-based telephony in the late 1990s. Despite extraordinary technical breakthroughs, these systems were commercial failures, respectively resulting in losses of roughly \$5 and \$3.5 billion (de Weck *et al.,* 2004). The proximate causes of these failures were deterministic forecasts of market demand (ground-based cellular telephony rose rapidly in the mid 90s) and inflexible system architectures that could not be easily downsized or switched to different types of service or coverage. Therefore, strategic planning of engineering systems under uncertainty is very critical. In the academic literature and practice, real options and risk management approaches have been applied to mitigate this issue. Most of these applications focus on managerial flexibility and flexibility valuation using sophisticated financial mathematical formulas. The oil and gas industry faces additional challenges because decision makers have to define project scopes, select development plans, and make multi-billion dollar upfront investments while multi-domain uncertainty (e.g., geological, technological, and market uncertainty) is present and evolving. Offshore petroleum projects are an example of such capital-intensive projects, which require integration of multiple disciplines (e.g., geosciences, reservoir engineering, facility engineering, and project economics) and decision-making under various technical and market uncertainties.

However, engineering systems are generally so complex that straight forward application of real options and risk management methods to the projects often does not yield much insight into how to design flexibility into systems such that these systems can adapt to future uncertainty. Identification of the interactions and uncertain factors of important sub-domains requires sound methodologies and a lot of effort. Traditional engineering practices are very domain-oriented and generally assume that the interactions with other domains are known or negligible. Much of the real options and risk management literature does not handle the design of engineering systems and simply treats technical systems as a black box (Trigeorgis, 2002; Copeland and Antikarov, 2003). Therefore, there is a research need to fill this gap: to develop a framework and methods for identifying and analyzing flexible strategies in complex engineering systems under multi-domain uncertainty. Wang (2005) proposed the use of screening models to identify critical uncertain variables and ranges of flexibility in systems. However, the screening model in Wang (2005) was a low-fidelity non-linear programming model. This work represents an emerging body of literature referred to as real option "in" projects (Wang and de Neufville, 2006). This thesis further advances the screening model approach by developing a systematic framework to explore multi-level flexibility in engineering systems under multi-domain uncertainty. It demonstrates this approach and framework for development planning of offshore petroleum projects.

## 1.2 Capital-intensive Infrastructure Development Planning

Engineering Systems is a new field of research (Moses, 2004), which includes technical, managerial, and social dimensions and their interactions. Development planning of engineering systems, such as for capital-intensive manufacturing infrastructure, transportation systems, and oil and gas production facilities, shares similar challenges:

- Long lifecycles: the typical lifecycle of engineering systems, from design, development, and operation to abandonment, easily spans several decades (e.g., 20~50 years for offshore petroleum projects, the Whiting refinery[1] is over 100 years old).
- Capital-intensive: development of engineering systems requires large capital investment. For example, public transportation systems and offshore petroleum systems require billions of dollars of investment before systems can become operational.
- Evolving internal and external uncertainties: within the long lifecycle, resource uncertainty, technical factors, and market environment will likely evolve. Future conditions very likely will be outside the range of initial estimates (e.g., reserve depreciations in North Sea oil fields (Watkins, 2000)).
- Complex interactions: development of engineering systems involves multiple domains (or disciplines), such as physical sciences, engineering, economics, and politics. Development planning not only requires natural sciences, engineering, and social sciences but also an understanding of the interactions among these domains.
- Significant economic and societal impact: the success or failure of engineering systems has significant economic and societal impact due to the amount of capital and people involved and the needs of an increasingly environmentally sensitive society.

Offshore oilfield exploration and production projects are good examples to illustrate the challenges of capital-intensive infrastructure development. The lifecycle of offshore deepwater oilfield projects (exploration, appraisal, development, operation, abandonment) usually spans 20~50 years, within which both technical factors (i.e., reservoir composition, production/drilling technology) and market conditions (i.e., oil/gas price, material/construction cost) evolve. The field exploration and appraisal stages require millions of dollars in investment for seismic and exploration/appraisal well drilling to identify, quantify, and verify the existence of hydrocarbons. In the development stage, billions of dollars of infrastructure investment (such as oil platforms,

[1] BP refinery history by Junaid Ansari.
http://www.aiche.org/uploadedFiles/FPD/Uploads/Docs/BP%20Whiting%20Oil%20Refineryd.doc

wells, subsea equipment and pipelines) have to be made before any oil can be extracted and shipped to market. A petroleum project generally includes the following stages for its lifecycle: Exploration → Appraisal → Concept Study → Execution → Production → Abandonment. Oil firms use different names for these phases but they generally contain similar tasks and decisions. During the appraisal and concept study stages, the development decisions, such as the location of platforms/wells, substructure type, platform capacity, and number of wells, need to be made while significant amounts of subsurface and market uncertainty are present and evolving. An improper or rigid development plan can cause a loss of opportunity in the future or incur unnecessary capital expenditures. As a result, the investment and operating companies carry a significant amount of risk. Furthermore, development planning needs to integrate information from multiple domains, such as sub-surface descriptions, wells, facility designs, and project economics. Successful development planning for capital-intensive infrastructure projects requires a holistic perspective of the inter-connected systems and uncertainties.

Degrees of freedom for future changes are mostly determined by the decisions made in the early design stages. A deterministic design without provisions for future changes is unlikely to be as successful as it could be given the various uncertainties. Many examples show the need to consider future uncertainty in development planning stage. For example, Figure 1 shows the evolution of reserve Appreciation Factors (AF) for three oil fields (i.e., Valhall, Tartan, and Beryl) in the North Sea. Reserve AF is defined as the ratio between the future (actual) and initial (priori) reserve estimates. These three examples give three different evolution trajectories for reserve AF. Valhall's AF continuously increased up to 4 within 24 years; the AF for Tartan dropped to 0.5 within the first year and then remained relatively stable over the next 20 years; Beryl's AF had two discrete jumps (i.e., in years 1979 and 1992), which boosted the AF up to 3 within 15 years. These examples demonstrate that reserve estimates indicating the quantity of hydrocarbons available to be produced over time can be significantly different (e.g., 50% ~ 400% of the initial values) from the initial estimate. Therefore, decisions based on an initial fixed estimate may potentially limit the value of a development and production project.

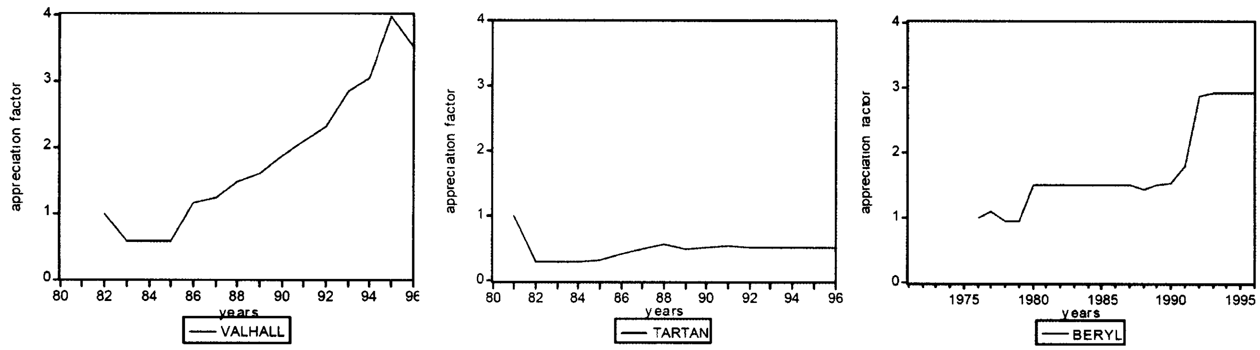


**Figure 1:** Reserve Appreciation Factor for three oil fields in the North Sea
(Figures are adapted from Watkins, 2000)

Other examples of capital-intensive infrastructure include manufacturing systems (for automobiles and aircraft), public transportation infrastructure, and energy systems (power plants, dams, electrical power grids). All of these share similar challenges: long lifecycles (>10 years), large irreversible investments (>$10 million), and large requirements or usage uncertainty (>10% volatility per annum). Thus, during the early stages of a project, system architects and decision makers need a systematic framework and modeling and simulation tools to explore the opportunity for embedding flexibility into these systems such that they can be evolved under multi-domain uncertainty. This is the key motivation for this thesis.

## 1.3 Uncertainty and Flexibility

Uncertainty reflects the fact that many assumed inputs for system design, such as customer demand, commodity prices, amounts of available resources, are random variables. For example, the exact volume of hydrocarbon reserves in a field is not known ahead of time, and thus probabilistic estimates are needed. There are many uncertain factors in the development of capital-intensive infrastructures. They can be classified into three groups:

- **Endogenous uncertainty** is deeply embedded in the technical systems, such as the geological and production technology performance uncertainty in petroleum projects. Understanding this type of uncertainty requires domain knowledge of the technical systems. Systems architects can actively manage and thus reduce endogenous uncertainty by investing in uncertainty reduction. For example, in petroleum projects, subsurface uncertainty can be reduced somewhat by seismic analysis and appraisal well drilling.

- **<u>Exogenous uncertainty</u>** is outside of the direct control or influence of decision makers and system architects. Examples of exogenous uncertainty include environmental regulations, customer demand, and market uncertainty. Decision makers and system architects can respond to exogenous uncertainty proactively or reactively, but this type of uncertainty originates from the external environment (outside the projects system boundary) and cannot be reduced at the source by decision makers. However, this does not mean that nothing can be done about the exogenous uncertainties during the design phase. Decision makers can manage their impact by building real options (i.e., flexibility) into the projects and technical systems.
- **<u>Hybrid uncertainty</u>** is the type of uncertainty jointly determined by systems' endogenous and exogenous factors. Decision makers and system architects can have some level of control over these uncertainties. In offshore petroleum projects, hybrid uncertainties are determined jointly by reservoir, facility, and market uncertainties. Examples include development cost and schedule uncertainty, as well as contractual uncertainty.

A similar way of classifying uncertainty has been proposed in the literature. Lessard (2001) proposed the layers of uncertainty as shown in Figure 2. From the inner rings to outer rings, a company's ability to influence the uncertainty is reduced. In this layer of uncertainty model, the inner ring (i.e., technical/project) uncertainty corresponds to endogenous uncertainty which companies can directly control or manage; the three outer rings' uncertainty (i.e., country/fiscal, market, and natural events) corresponds to exogenous uncertainty which companies can not directly influence or control; the second inner ring's uncertainty (i.e., industry/ competitive) corresponds to hybrid uncertainty which companies can partially influence.

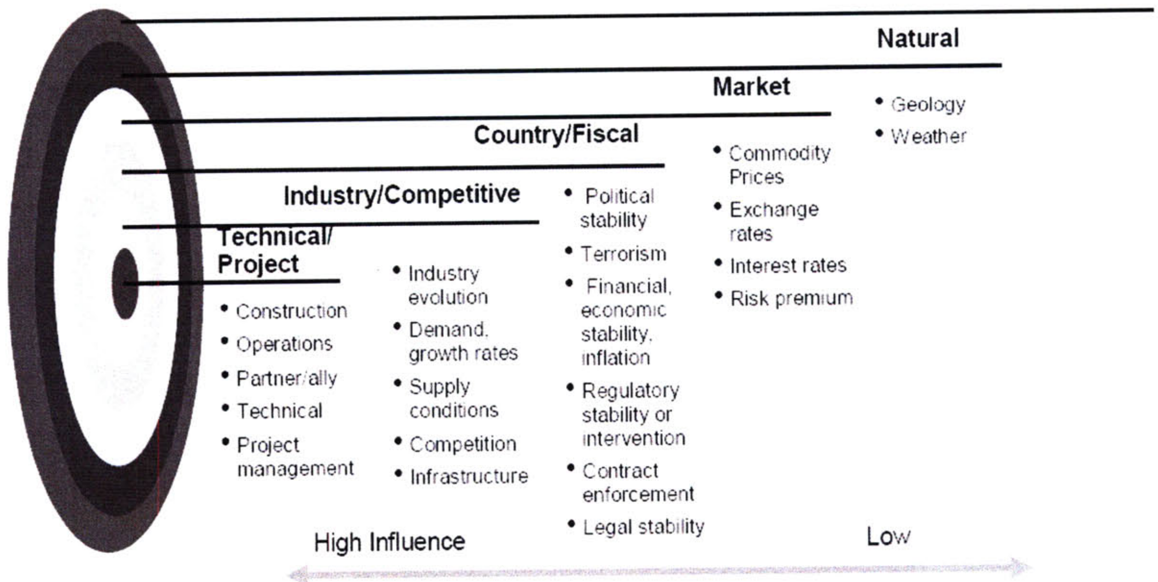


**Figure 2**: Layers of Uncertainty
(Figure according to Lessard, 2001)

Uncertainty has long been identified as an important factor in the design and development of complex engineering systems. Various stochastic modeling techniques have been proposed to simulate the evolution of uncertainty variables, such as the Geometric Brownian Motion (GBM) model and the lattice model for simulating demand and market uncertainty. But most of the uncertainties considered are projects' exogenous uncertainty, such as demand and market price uncertainty. Also, in much of the literature only one dominant uncertainty at a time is considered.

In general, there are three approaches to management of uncertainty:

- Control uncertainty: Some uncertainty can be directly managed or reduced by investment in uncertainty reduction. For example, sub-surface uncertainty can be reduced for petroleum projects by investment in seismic and appraisal well drilling. Demand management is another example of this kind of control uncertainty. By adjusting the price or quality of service provided by a system at different times, it is possible to increase or decrease the demands on this system. Stochastic process control (SPC) is another example of uncertainty control. Statistical analysis is applied to process data to identify root causes of variation and then implement variation reduction methods. Controlling uncertainty directly intervenes and manages uncertainty at the source, and it does not generally require modifying system configurations. Thus it attempts to minimize adverse impacts of uncertainty. Controlling uncertainty at its source is important during system operations but is generally less of an issue during system design.

- Re-active approach: Systems are designed with the capability to handle uncertainty within a certain range. Robust design is one example of the re-active or passive approach to handling uncertainty. Robustness of a design is the property of a system that allows it to satisfy a fixed set of requirements, despite changes in the environment or within the system (i.e., in the presence of noise factors). Robust design implies de-sensitizing the systems' performance to changes in the environment. For example, the robust parameter design approach is applied to reduce the variability in performance of products and processes in the face of uncontrollable variation (uncertainty) in the environment, manufacture, internal degradation, and usage conditions.
- Pro-active approach: The real options literature falls into this category. The pro-active approach designs flexibility into projects or systems, which allows the projects to adapt to uncertainty, exploiting upside opportunities, while mitigating downside risks. For the pro-active approach, flexibility is the main mechanism to handle uncertainty. *Flexibility is the relative ease with which changes can be made to a system.* Thus, flexibility is a relative property comparing one or more designs against each other. However, there are two categories of flexibility: one is managerial flexibility on projects, the other is design flexibility in systems. Real options "on" projects deals with managerial flexibility, such as wait, deferment, abandonment options at each stage of a project. Real options "in" projects look into technical systems and identify system design strategies that enable project flexibility. Following the introduction of the concept of flexibility, a detailed differentiation between real options "on" and "in" projects will be discussed.

Flexibility has become a very popular concept in the engineering academic literature and in practice. However, it can mean different things if the context changes. Saleh *et al.* (2008) give a good multi-disciplinary literature review of flexibility and propose a research agenda for designing flexible engineering systems. The concept of flexibility is developing in different realms:

- In decision theory, flexibility is the number of remaining alternatives after previous commitments are made: more remaining choices reflects increased flexibility.
- In manufacturing systems, research on flexibility has grown dramatically over the past 30 years. The major focus of the literature is on defining and classifying different types of flexibility for manufacturing systems (e.g., Sethi and Sethi, 1990, Hauser and de Weck 2007), such as volume flexibility, routing flexibility, expansion flexibility, and product mix flexibility. There are also discussions of strategic flexibility (Evans 1991, Koste and Malhotra 1999) and operational or tactical flexibility (Barad and Sipper 1988). The former refers to flexibility at the plant or business unit level whereas the latter refers to flexibility at the machine level.
- In the management literature, a growing literature addresses the concept of flexibility in relation to investment decisions and market uncertainty. Flexibility is introduced in this context to give decision makers managerial flexibility as a way of dealing with market uncertainty. Managerial flexibility is defined as the ability of management to adjust the course of a project by acting in response to the resolution of market uncertainty over time. A growing body of literature, called Real Options, is based on the financial options theory, and is applied to calculate the financial value of managerial flexibility. Real options give management the right but not the obligation to take certain courses of action to react to market uncertainty. Standard finance mathematics, such as the Black-Scholes formula and the binomial tree, have been applied to calculate the financial value of managerial flexibility, but real options theory does not generally reveal how to achieve such flexibility and where to embed flexibility through engineering design. As a result, this type of application is called "real options 'on' projects" (Wang 2005). The expression reflects the fact that this type of real options treats an entire project as a financial entity without looking into engineering design flexibility.
- An emergent body of literature (Kalligeros, 2006; Wang & de Neufville, 2005; Wang, 2005; de Neufville, 2003) addresses flexibility in engineering system design. Design flexibility differs from managerial flexibility that is emergent or coincidental in the development and operation of a system; design flexibility has to be anticipated, and designed and engineered into systems. Design flexibilities are the real options "in" projects. Real options "on" projects are financial options taken on technical systems,

treating technical systems as "black boxes". Real options "in" projects on the other hand are options created by design, which enable systems to be easily changed or modified to satisfy future needs. As a result, it requires deep understanding of both technical systems and project economics, but analysts with primarily a financial background are not generally equipped for this task. For example, designing real options into offshore oil and gas production facilities requires both technical understanding of the systems (e.g., reservoir characteristics and dynamics, oil/gas/water separation processes, and facility designs) and economic analysis of the design (e.g., CAPEX and OPEX estimates, Production Sharing Agreement modeling, and project economics evaluation).

- Instead, system architects and engineers are responsible for identifying where and how to embed design flexibility and for implementing such design flexibility. It is not an easy task to identify design flexibility in complex engineering systems, given multi-domain uncertainty. This requires a novel approach to searching and screening for flexible design strategies. De Weck et al. (2003) have suggested alternative programmatic approaches and technical designs for the Iridium and Globalstar systems in which flexibility could have been created through staged development; Wang (2005) used mixed-integer stochastic programming to value path-dependent options in river basin development; Kalligeros (2006) developed a method—Invariant Design Rules (IDR) -- to identify which elements of an oil platform can be flexible while achieving a high degree of commonality among a sequence of platforms. Elsewhere, Zhao & Tseng (2003) have investigated the flexible design of a simple building, a parking garage with enhanced foundations and columns that can be expanded to cover local parking demand. Although the research on designing real options "in" capital-intensive engineering systems emerged relatively recently, the concept of building flexibility into systems to improve systems' economic value under uncertainty has been developing and evolving (e.g., Denso Panel meter example in Whitney, 2004; Sethi and Sethi, 1990) over the past few decades in the manufacturing / product development research domains. However, designing real options into capital-intensive engineering systems is more complex than a single production or manufacturing systems for consumer products due to the complex interactions of multiple disciplines, large irreversible investment, systems' long lifecycles, and multi-domain uncertainty. Thus, holistic approaches to explore and design real options "in" complex capital-intensive engineering systems under multi-domain uncertainty remain somewhat elusive.

## *1.4 Research Opportunity*

This research addresses a research gap between traditional engineering design and real options applications on capital-intensive infrastructure projects. There are many papers in the areas of engineering system design under uncertainty. Chapter 2 will give a detailed literature review. In this section, we select the six most relevant papers for detailed review and identify a research gap: using a simulation approach to explore and evaluate flexible solutions (or architectures, strategies) under multi-domain uncertainty.

**Table 1:** Selected 6 key papers related to this thesis

| | **Authors /Years** | **Journal /conference** | **Main topic** | **Limitations** |
|---|---|---|---|---|
| **(a)** | de Weck, de Neufville, and Chaize (2004) | Journal of Aerospace Computing, Information, and Communication | Staged deployment of communication satellite systems | • Only considers market/demand uncertainty |
| **(b)** | Wang and de Neufville (2006) | International Council on Systems Engineering (INCOSE) | Real options "in" projects /concept of using screening models | • Low-fidelity nonlinear programming model<br>• discrete values for uncertain variables<br>• no systematic framework for screening |
| **(c)** | Dias (2004) | Journal of Petroleum Science and Engineering | Overview of real options models for valuation of E&P assets | • simple business model (NPV=qBP-D)<br>• options pricing model<br>• real options "on" projects |
| **(d)** | Lund (2000) | Annals of Operations Research | Valuing Flexibility in Offshore Petroleum Projects using stochastic programming | • Reservoir uncertainty is very simplified (H-M-L).<br>• no facilities / cost model<br>• no configurational flexibility |
| **(e)** | Goel and Grossmann (2004) | Computers and Chemical Engineering | Planning of offshore gas field developments under uncertainty in reserves | • Only reservoir uncertainty considered<br>• Point-optimal solution (stochastic programming) |
| **(f)** | Saputelli *et al.* (2008) Halliburton | Society of Petroleum Engineers | Integrated Asset Modeling for making optimal field development decisions | • Integration based on high-fidelity models, computational intensive<br>• Point-optimal solution |

Table 1 shows the six selected papers. For each paper, the authors, sources, main topic, and limitations are illustrated. This thesis is building on top of the existing literature and further develops a screening model approach for designing flexible engineering systems under multi-domain uncertainty.

a) de Weck *et al.* (2004) propose a flexible staged deployment strategy for communication satellite systems when market and customer demand is uncertain. An integrated flexibility evaluation framework, which interconnects a stochastic customer demand model, satellite architecture designs, a lifecycle cost model, and program economics evaluation, was developed. The main limitation of this paper is that it only considers the system's exogenous uncertainty (i.e., market/customer demand). The systems' endogenous uncertainty (i.e., technical uncertainty) is not taken into account.

b) Wang and de Neufville (2006) develop a two-stage process – a screening model and simulation model – to identify and evaluate real options "in" engineering systems. The main limitations of this paper include: First the screening model in this paper is a low-fidelity nonlinear programming model. Secondly, the uncertain variables are assumed as several discrete values instead of full probability distributions. Thirdly, the screening model in this paper is only used to identify key uncertainty variables. Moreover this paper does not yet provide a systematic framework for how to develop and apply screening models for exploring and evaluating different types of flexibility in engineering systems.

c) Dias (2004) reviews real options models in petroleum exploration and production projects. This paper summarizes a stream of literature – real options "on" petroleum projects. There are several key limitations in this approach: First, technical systems (e.g., reservoir, facility) and are not modeled at a level of detail to capture the feedback loops among multiple disciplines. For example, the business model for a petroleum project is low fidelity ($NPV = qBP - D$, where $q$ is the value quality factor for the reserve (~33%, "one-third rule of thumb"), $P$ is price of hydrocarbon; $B$ is number of barrels in the reserve; $D$ is development cost) and thus it does not capture material, logical, and financial flows (feed forward and feedback) among reservoir, facility, and project economics. Secondly, reservoir volume uncertainty is modeled as a static probability distribution and as such does not capture the evolutionary nature as human perception of reserves evolves over time. Thirdly, the main purpose of this paper is to focus on real options valuation using various financial option models. While useful in its own right this paper does not show how to identify flexibility in design and how to evaluate the value of flexibility using technical-economical models.

d) Lund (2000) develops a stochastic dynamic programming model for development planning of offshore petroleum projects. The main components for the optimization model include a simple representation of reservoir production ("tank model"), as well as facility capital and operating cost inputs. This paper discusses different types of flexibility (e.g., flexibility to drill exploration wells, flexibility to expand platform capacity) and multi-domain uncertainty (i.e., reservoir volume, crude oil price). This paper is the closest relevant paper to this thesis. However, this paper made a number of significant simplifying assumptions: First, the sub domains were not modeled at a similar level of detail. For example, there is no facility model, and CAPEX and OPEX for different development scenarios are assumed as fixed inputs. Thus, this model does not properly capture the dynamic coupling between reservoir and facility. Secondly, reservoir uncertainty is highly simplified as three discrete values (High-Low-Mean). This paper also doesn't make a distinction between the true (unknown) reservoir volume and the evolution of human estimation of the value of reserves on which decisions are based. Thirdly, this paper doesn't model architectural complexity and flexibility, such as evolving configurations for multiple facilities and multiple reservoirs in a hydrocarbon basin. The case study shown in this paper only considers a single reservoir and a single facility.

e) Goel and Grossmann (2004) develop a stochastic programming approach for planning offshore gas field developments under reserve uncertainty. Different from Lund (2000), this paper models the optimal field development decision for a hydrocarbon basin with multiple fields and facilities. The main limitations of this paper include the following: 1) The model only considers reservoir uncertainty and facility and market uncertainty are not modeled and taken into account in the decision space. Reservoir uncertainty is modeled as three discrete values (i.e., high-low-medium) for cumulative production and initial deliverability. 2) The system model (reservoir, facility, and economic models) is of low fidelity, in which the oil production rate is assumed to be a linear function of cumulative oil production. Furthermore, the couplings between reservoir, facility, and economics are not captured. 3) A stochastic programming algorithm is used to search for an optimal static solution instead of a flexible solution under uncertainty, thus, the optimal solution may not be optimal if model assumptions are wrong or more realistic uncertainty models are considered.

f) Saputelli *et al.* (2008) summarize the current practice and new trends in oilfield development planning under uncertainty. In contrast to a traditional discipline centric approach, this paper proposes an integrated asset modeling framework for optimal field development decision making under uncertainty. Although this paper represents the state-of-art in industry practice, this paper has the following limitations: First, this paper represents the integration of multiple disciplines using high-fidelity models, which may be impractical due to the computational effort required for optimizing a large number of alternatives during a project's early stages. Secondly, this paper uses the same modeling approach (i.e., probability distributions) to model uncertainty for subsurface, surface, and economic parameters, but this approach does not model and simulate the evolutionary trajectories for these uncertainty variables during the long lifecycle of a project. Thirdly, this paper focuses on finding optimal development strategies by comparing them in a mean-variance plot, but flexibility in design, which can potentially shape the distribution of outcomes, is not exploited.

Traditional engineering design optimizes a system's performance given deterministic future scenarios. In general, rigid and point-optimized solutions do not perform well when both endogenous and exogenous uncertainties are high. If the future uncertainty turns out to be favorable, point-optimized solutions are too rigid to be expanded and modified, which causes a loss of opportunity. If the future uncertainty turns out to be unfavorable, point-optimized solutions cannot easily be reduced in scale, which wastes capital.

Real options provide a new method for resource allocation and investment planning under uncertainty. Compared to the discounted cash flow approach, the real options approach takes into account the value of managerial flexibility. However, most of the applications focus on valuation of managerial flexibility using financial option mathematics, while technical systems are simplify treated as black boxes. The more challenging questions, such as where to embed flexibility and how to screen and differentiate among different flexible strategies still remain. These questions are challenging for complex engineering systems due to the following reasons:

- Complex engineering systems include many subsystems and their interactions. Identifying where to embed flexibility from a large numbers of possibilities is not an easy task. In general, because the design space for possible flexible strategies can be on the order of billions of possibilities, an exhaustive search and evaluation of the design alternatives is computationally expensive if done by using domain-specific high fidelity models and tools. Optimization-based approaches (e.g., Goel and Grossmann, 2004; Saputelli *et al.,* 2008), can guide the search more effectively, but they tend to lead designs to rigid point-optimal solutions instead of flexible solutions. Therefore, there is a need for a computationally effective search strategy for design flexibility. In recent literature, screening models (de Neufville, 2008) have been proposed as a way to identify flexible strategies and designs. Screening models trade details for speed.
- Complex engineering systems have multi-domain uncertainties. Design flexibility has to be able to handle systems' endogenous and exogenous uncertainty effectively. Many papers only deal with either a system's endogenous uncertainty (e.g., Goel and Grossmann, 2004) or exogenous uncertainty (de Weck, 2004). Although some papers start to consider both technical and market uncertainty, the technical uncertainty is simply treated as static probability distributions (Dias, 2004; Saputelli *et al.,* 2008) or several discrete values with pre-determined probabilities (Lund, 2000; Wang and de Neufville, 2005). The time-varying nature of technical uncertainty (e.g., evolution of reserve estimates) is not clearly modeled. The identification and modeling of a system's endogenous uncertainty requires technical knowledge of the systems and their operating conditions. Decisions are made based on human perception of the uncertain variables instead of the true underlying values for the variables. For example, the development of an oilfield project is sized according to human perception of the recoverable hydrocarbon volume instead of the true underlying value, which is unknown during the development and planning phases. Many of the papers (Dias, 2004; Lund, 2000; Goel and Grossmann, 2004) in the literature do not make such distinction. The literature in the petroleum

engineering domain discusses technical systems and their uncertainty in great detail, while market conditions are assumed as given deterministic inputs or some static probabilistic distributions. Furthermore, the standard real options literature focuses on managerial flexibility (Trigeorgis, 2002) and its evaluation using financial option models (Copeland and Antikarov, 2003) under market uncertainty. The standard real options literature usually treats the technical system and its uncertainty as a "black box." Therefore, a holistic uncertainty management approach for multi-domain uncertainty still remains to emerge.

Therefore, this research is designed to address the following topics:

- How to explore flexible strategies in the engineering systems' planning stages.
- How to take into account multi-domain uncertainty in screening of flexible strategies.

The thesis develops a method to develop integrated screening models at the mid-fidelity level, which capture the key components of subsystems and their interactions. The level of detail for such a mid-fidelity model is determined by both engineering experience and quantitative analysis, such as Design of Experiments (DOE) or sensitivity analysis to identify important factors for the model. A mid-fidelity screening model needs to achieve an appropriate level of detail such that the rank order of different strategies can be established with relative confidence. Compared to domain-specific models, these screening models are computationally inexpensive to run, which allows searching for flexible strategies in the large design space more effectively in the engineering systems' development planning stage. Secondly, this thesis provides a simulation-based approach to assess the value of different levels of flexibility under multi-domain uncertainty. The development of these methods is applied in the context of offshore petroleum production projects.

## 1.5 Contributions

As summarized in Section 1.4, this research is designed to answer the following research questions:

**Research questions:**

1. How to model and explore flexible strategies in the planning stages of capital-intensive complex systems in a computationally efficient way?
2. What is a general framework for modeling, simulating, evaluating, and comparing different strategies with varying degrees of flexibility under multi-domain uncertainty?

In order to address these two research questions, two key methodologies are developed in this thesis:

***(1) The use of screening models to explore promising flexible designs.***

Complex engineering system design involves many domains and their interactions. Each domain has its own design variables and constraints. The cross-domain interactions are not easily captured by traditional engineering practice. Domain-specific models and tools are generally very detailed and computationally expensive. For example, each run of a full-scale oil field reservoir model (such as models by commercial reservoir simulators, e.g., VIP by Halliburton, ECLIPSE by Schlumberger) can take several hours or even days, given the computational resources available to engineers. A search for multiple possible flexible designs would require from thousands to millions of runs, and the computational time (weeks or months of simulations) required for such a search is not acceptable for strategic decision making in a competitive environment. Although several weeks or months for simulations seem like a very short period when the lifecycle of an oilfield spans several decades, the time pressure for making decisions during the concept study and development planning phases is usually very high, and system architects usually do not have freedom to extend a project phase for a few months to run more scenarios when the project pace is partially determined by senior management at the cooperate level (e.g., timeline for first oil) or by joint-partners in a Production Sharing Agreement (PSA) context. Even though an extended study may be very valuable from an engineering stand point, there generally is a lack of formal approaches to quantify the cost and benefit of extending a project's schedule for further study. Furthermore, the current discipline-based modeling approach in the petroleum industry requires significant amounts of time for model setup or data transfer between different tools (e.g., typically 2/3 time[2] is spent on transferring data among different discipline-based tools and setting up models properly, 1/3 of time is spent on actual computation and analysis). Thus, the disconnected high-fidelity models are typically not capable to support quick evaluations during concept study and planning phases when a large design space needs to be explored.

The advantage of using mid-fidelity screening models during a project's early stages includes: First, it reduces the simulation time for each run from hours or days to seconds, thus, it becomes computationally feasible to run Monte Carlo simulations to evaluate strategies under multi-domain uncertainty. Figure 3 (a) shows the approximate tradeoff between computational effort and model fidelity. Mid-fidelity models significantly reduce computational time while retaining a level of detail to ensure that the relative rank order of different design alternatives can be trusted within the known range of model assumptions. Integrated mid-fidelity models are used as a screening tool during the early stages of a project. Secondly, the integration among multiple disciplines reduces the data transfer and model setup time, and it also ensures data integrity by avoiding potential errors in the manual processes. Thirdly, the integrated screening model captures important feed forward and feedback loops among different disciplines. These couplings are not usually captured in the disconnected discipline-based tools. Finally, the approach enables modelers to update the screening model to when new information (e.g., updated reservoir characteristics, new reserve estimates) becomes available during a project's early stages. For high-fidelity models, it may take days, weeks, or months to update and setup such models. Therefore, screening models are more appropriate for exploring a large design space and identifying promising strategies during the early stages of a project. Overall, mid-fidelity models achieve a balanced tradeoff between computation time and model fidelity. Figure 3(b) shows another tradeoff (Thomke, 2003) between timeliness of (simulation) results and model fidelity. A low-fidelity model is easy to set up and can run very fast but the accuracy of the results is also generally low. A high-fidelity model requires significant amount of time and resource to develop and simulate, but the results it produces may be highly accurate (compared to reality). In between, a mid-fidelity model achieves a good balance between timeliness and

[2] This data is based on an informal survey of senior engineers in a major oil company.

accuracy of results. The choice of model fidelity would depend on "affordability" (or cost/benefit) of spending time acquiring more information, including more detail, running simulations, and waiting for results.

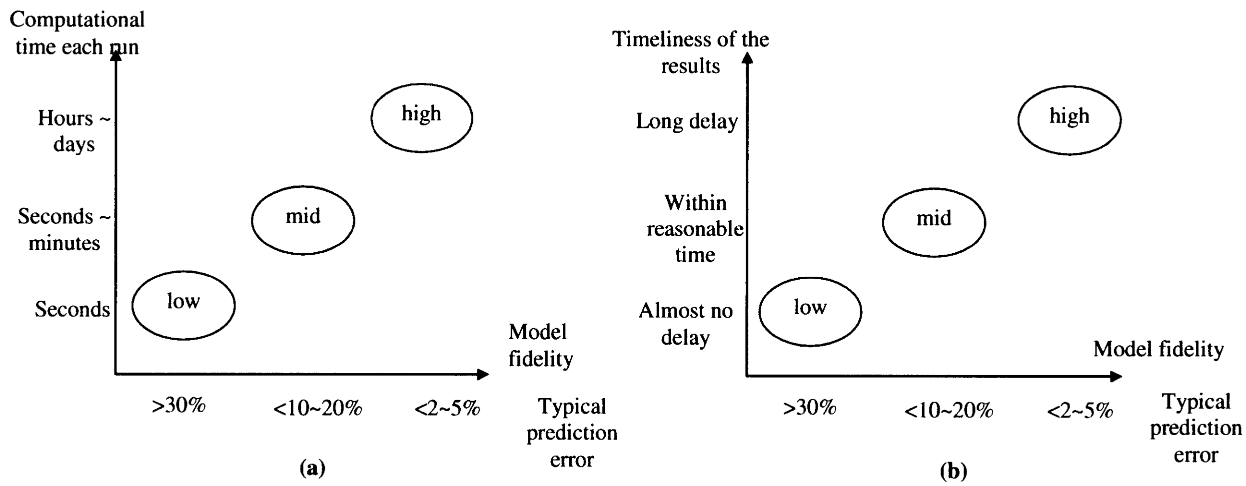


**Figure 3:** (a) Computation time vs. Model fidelity; (b) Timelines of results vs. Model fidelity

The screening model is a simplified representation of a system, which captures the essential domains and their interactions in an integrated way. The use of screening models is proposed to serve this purpose. However, the screening models are not the end goal in themselves. Figure 4 shows two sequential phases: the screening phase involves using mid-fidelity screening models to identify promising flexible strategies or designs; the detailed design phase involves designing and evaluating the preferred designs by using high-fidelity domain models to verify the preliminary design decisions. Given the complexity of engineering systems, it is an intellectual challenge to identify the key elements to be included in integrated screening models. This thesis therefore focuses on the first step.

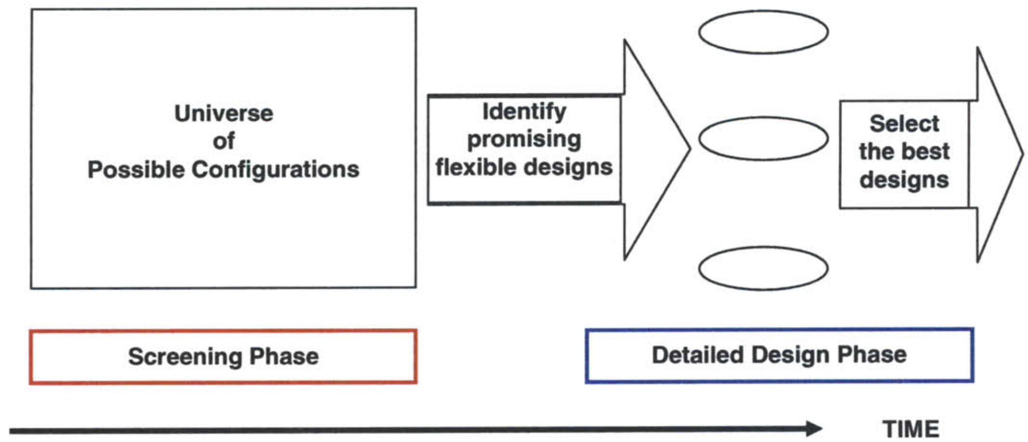


**Figure 4:** Screening models help identify promising flexible designs for detailed analysis and design (Figure is adapted from de Neufville *et al.*, 2008)

Figure 5 shows the two sub-processes during the screening phase. The first process is *strategy synthesis*, which defines a set of feasible strategies given the natural technology, economic and political context, and stakeholders' requirements. Strategy synthesis identifies a set of feasible initial strategies (or architectures) given the initial conditions, but the evolution of uncertainty and the response of these strategies (e.g., exercising various types of built-in options) is not yet modeled. This can be done manually or by automatic search algorithms such as Object Process Network (OPN) (Koo, 2005). In this thesis, we identify a few initial configurations and then use Design of Experiments to investigate them further. The second process is *strategy evaluation under uncertainty*, which evaluates the identified strategies under multi-domain uncertainty. This thesis focuses on the second step in Figure 5 and proposes and demonstrates a generic four-step process and a computational framework to screen strategies under uncertainty. This is the second major contribution of this thesis.

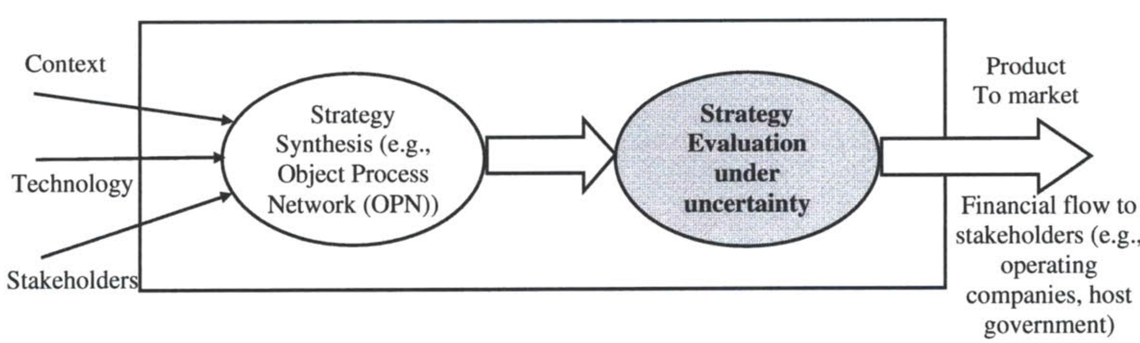


**Figure 5:** Two sub-processes in the screening phase

***(2) A Generic four-step process and a simulation framework to screening promising flexible strategies under multi-domain uncertainty.***

This thesis develops a generic four-step process for screening under uncertainty as shown in Figure 6. The four steps include modeling, strategy synthesis, simulation, and screening and analysis. This thesis demonstrates this four step process through the modeling and case studies in offshore petroleum projects. The details of these four steps will be illustrated in the rest of this thesis. We will summarize this generic four-step process in Chapter 8 Section 1.

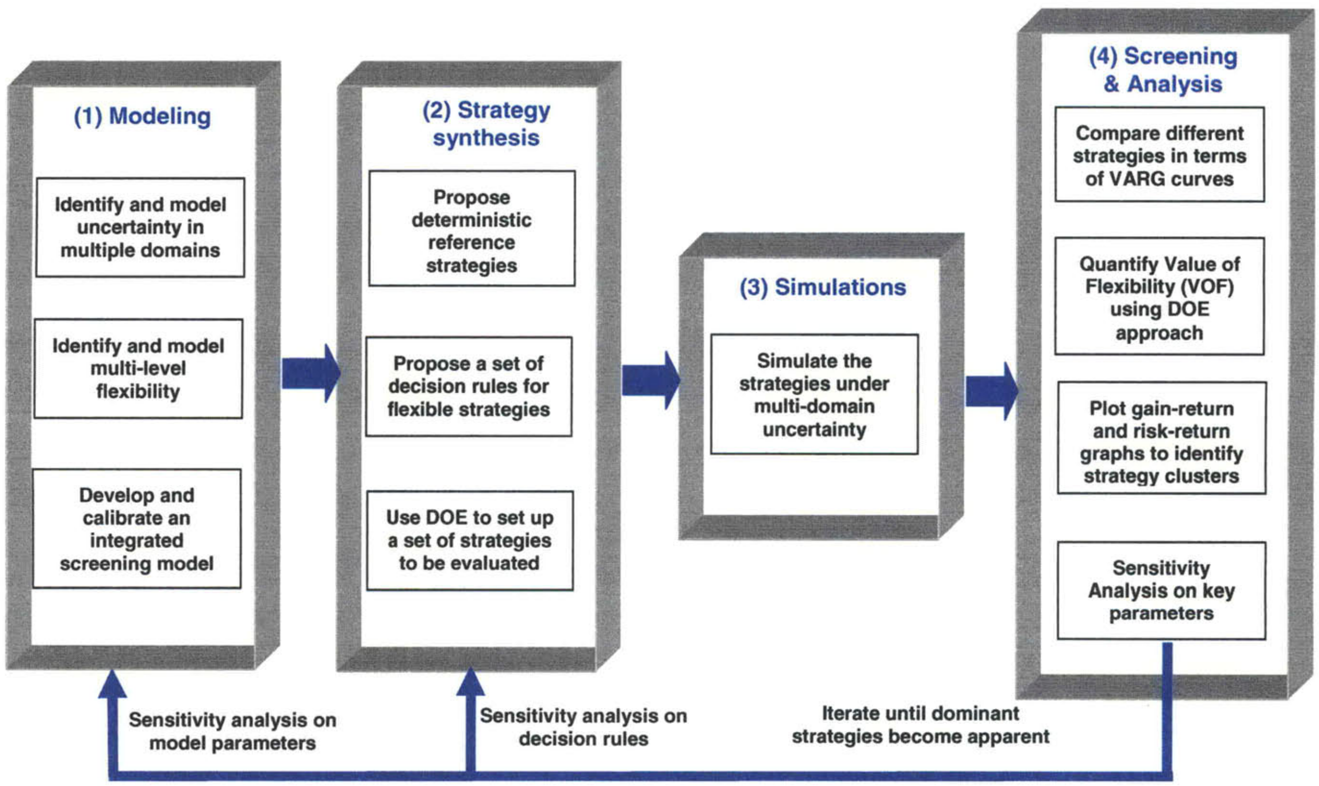


**Figure 6**: A generic four-step process for screening flexible strategies under uncertainty

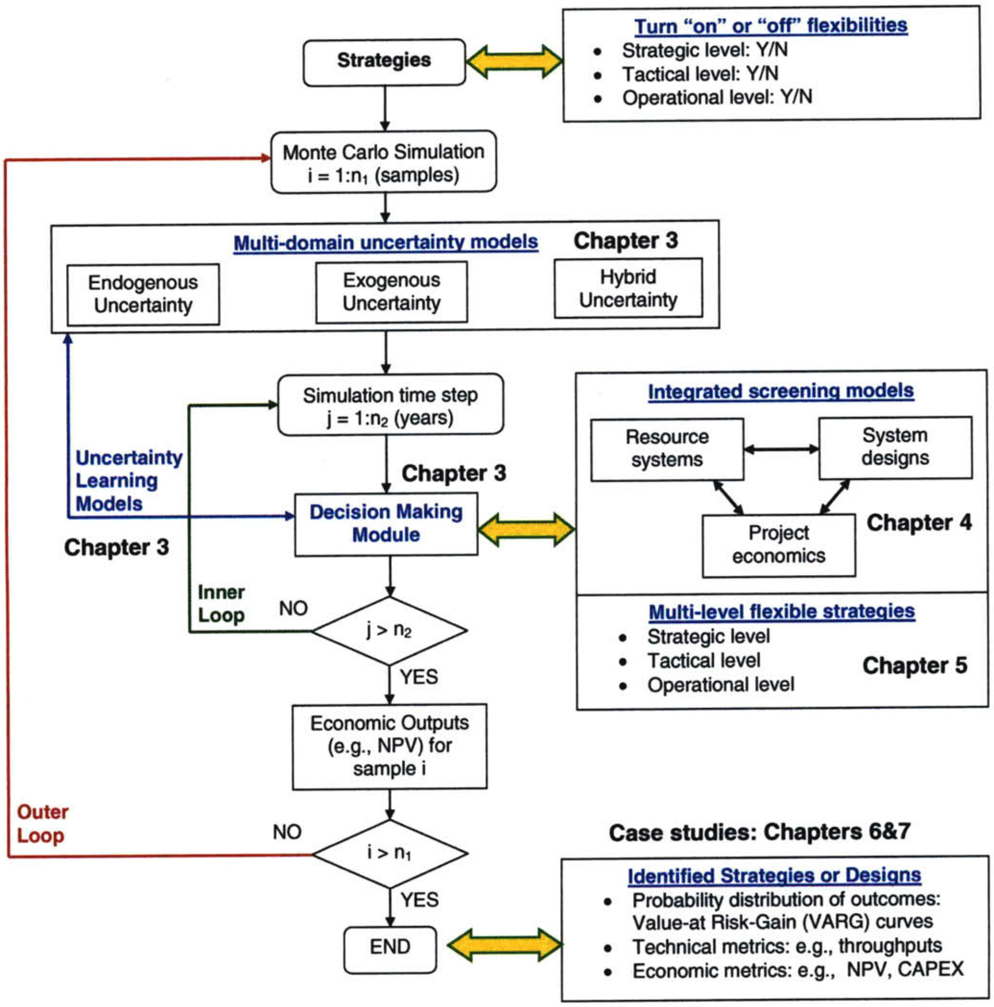


**Figure 7:** A simulation framework for screening strategies under multi-domain uncertainty (and thesis roadmap)

Figure 7 shows the integrated simulation framework. This is the framework that is executed during step (3) of the four step process in Figure 6. There are two iteration loops. The outer loop is a Monte Carlo simulation and each sample includes an instance of multi-domain uncertainty. The inner loop is a time-stepped simulation loop, which simulates the development and operation of engineering systems over their lifecycles. There is a decision making module built into the inner loop, which observes the evolution of multi-domain uncertainty and then modifies the state of the integrated screening models by exercising flexible strategies according to built-in decision rules. Hence, because the screening models are essentially time-variant, the resource systems and systems designs can be changed over the course of the simulated project lifecycle. After the completion of the simulation, strategies with varying degrees of flexibility and their designs are compared in terms of probability distributions of technical or economic metrics, such as Value-at-Risk-Gain (VARG) curves for Net Present Value (NPV).

The Value-and-Risk-and-Gain (VARG) diagram (Hassan and de Neufville, 2006) is a convenient way to display the distribution of possible results. It graphs the cumulative value associated with any possible design or strategy. It builds upon the Value-at-Risk (VAR) concept used by bankers to identify the risk of the losses they might incur. Figure 8 shows a VARG curve for a hypothetical project's NPV. Decision-makers may be interested in the probability of levels of Minimum and Maximum returns from a project. For example, one might want to know the possible downside with a 10% chance of occurrence, which is known as the "10% Value at Risk" (VAR). In Figure 8 this is -90 million dollars. Conversely, one might focus on the upside potential or "Value at Gain" (VAG). For example, the 10% VAG (corresponding to the complementary 90% VAR) is read at the 90% level of the vertical axis. There is thus a 10% chance that the net present value generated by from the system will be greater than 290 million dollars.

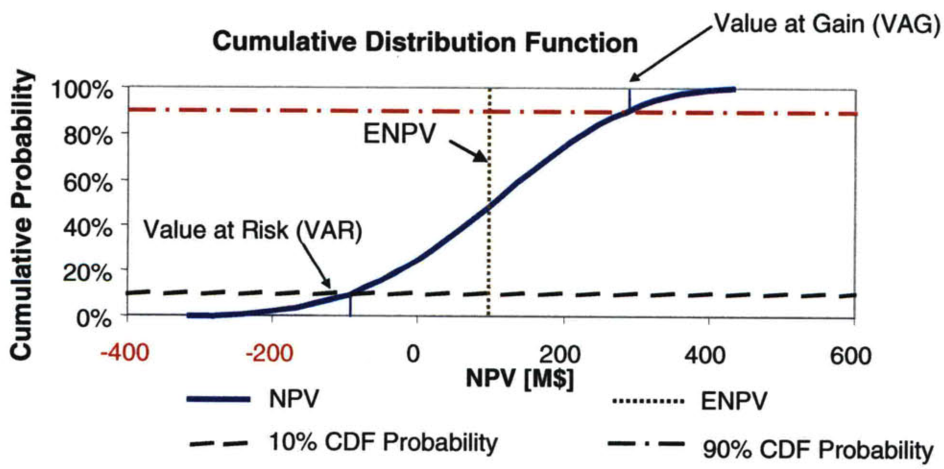


**Figure 8:** A Value at Risk and Gain (VARG) Curve for a Hypothetical Project

Many metrics can be read from a VARG curve. The ones that are most useful to decision-makers are the expected NPV (EPNV), and the maximum and minimum results. It is also possible to calculate the standard deviation (SNPV) which measures the dispersion of the distribution. Many designers use this measure to calculate the "robustness" of a system, that is, the degree to which its performance is affected by uncertainties. In some cases (such as the tuning of a radio) this is a good feature. In general, however managers prefer designs skewed towards upside gains, thus with high upside spreads, while maintaining small downside risks.

In order to generate the VARG curves, a simulation framework based on screening models is developed to evaluate different strategies under uncertainty during a project's conceptual study and development planning stages. Once promising strategies and designs have been identified, the discipline-based high-fidelity models can then be applied for design and evaluation during detailed engineering design (e.g., "define" stage in the oil and gas industry) stage.

A strategy is defined as a deliberate evolutionary path of a system's architecture under uncertainty. Under this framework, a strategy includes the following four key components:

- An initial configuration, which is identified by strategy synthesis processes as shown in Figure 5.
- A set of architectural paths along which the initial configuration could evolve.
- Evolutions of multi-domain uncertainty.
- A set of decision rules that trigger changes along the evolution paths starting with the initial configuration. The decision rules monitor the evolution of uncertainty and then exercise built-in flexibility if certain conditions are satisfied.

System designers have the ability to improve designs that have uncertain outcomes. The screening model approach enables designers to search for different flexibilities to shift the VARG curves to the right as much as possible by cutting the downside tail and extending the upside tail. By intelligently screening for, designing in and exercising flexibility in the form of real options throughout a system's lifecycle we may in fact "design" or at least influence the shape of the NPV distributions given a set of exogenous uncertainties. We do this typically by two complementary types of actions: one set reduces the downside tail, and the other set extends the upside tail. Overall, we attempt to increase the Expected Net Present Value.

We use the VARG graphs, complemented by a table summarizing several metrics extracted from the VARG curves, to help identify which strategies and their designs are most attractive for subsequent detailed designs. When higher values are toward the right, as in Figure 8, then configurations with curves and ENPV toward the right are preferred. Among two strategies, the better alternative is obvious if its curve lies entirely to the right of another. In general however, tradeoffs have to be made as it is rare that one design absolutely dominates all others. According to all metrics of interest, we wish to find the subset of non-dominated flexible designs and strategies.

Embedding flexibility in design gives system designers different ways to "shape" the VARG curves. The screening model and simulation framework provide a computational environment to search for better strategies. The VARG curve approach gives decision makers and system architects a quantitative way to compare different strategies under uncertainty. This thesis develops a prescription for such an integrated computation framework with key elements such as: screening models, multi-domain uncertainty models (and their learning), decision rules, and multi-level flexibility (e.g., strategic level, tactical level, operational level). The generic process and simulation framework are demonstrated through case studies in offshore petroleum field development projects.

## 1.6 Thesis Outline

Chapter 2 provides a brief literature review of the basic concepts underlying this thesis: uncertainty, real options and flexibility, integrated screening models, and decision making under uncertainty first in general, and then as applied to the petroleum domain. A research gap is identified. Chapter 3 develops the integrated simulation framework to explore flexible strategies in engineering systems. Multi-domain uncertainty models and intelligent decision rules are illustrated. Chapter 4 proposes screening models as instruments to explore designs under uncertainty. This concept is demonstrated through development of screening models for offshore petroleum exploration and production projects. Chapter 5 defines multi-level flexibility over the lifecycle of capital-intensive projects. Examples of different levels of flexibility are shown for offshore petroleum projects. Chapter 6 and 7 apply the simulation framework to study two types of flexible strategies for offshore field development: flexible staged development for a single large oilfield, and tieback flexibility in deepwater for multiple small oilfields. Tieback flexibility is architectural level flexibility which defines the field architecture for a hydrocarbon basin (i.e., connections between facilities and oilfields). A final chapter summarizes the thesis, identifies potential opportunities for applying this approach to other capital-intensive engineering systems, and provides directions for future research. The final chapter summarizes this thesis and illustrates a generic four-step process for exploring flexible strategies under multi-domain uncertainty with screening models. Although this thesis only demonstrates this procedure in petroleum projects, we believe that this procedure is generalizable to other capital-intensive systems which share similar challenges (i.e., long lifecycle, interactions among multiple disciplines, irreversible investment, decision making under multi-domain uncertainty) as in offshore petroleum projects.

# Chapter 2 Literature Review

## *2.1 Introduction*

This chapter sets up the intellectual foundation for this thesis, drawing on both the academic literature and industrial practice. Since the problem statement of this thesis is multidisciplinary in nature, the literature reviewed in this section is drawn from multiple domains: systems modeling, uncertainty management, real options and flexibility, and domain literature on offshore petroleum project planning. First, we discuss systems modeling approaches in order to position screening models amidst the abundant academic literature. Screening models are used as a front-end tool for exploring and identifying promising strategies and designs, followed by a detailed engineering design and evaluation stage. In Section 2.3, relevant literature on uncertainty in engineering systems is reviewed. This review shows that a multi-domain uncertainty perspective on engineering systems design and development planning is still lacking. Effective uncertainty management becomes a very critical issue over the lifecycle of complex engineering systems. Section 2.4 reviews real options and flexibility as a proactive way to manage uncertainty. Two streams of literature are identified and compared: one is real options "on" projects, which treats technical systems as black boxes and focuses on the financial value of managerial flexibility under market uncertainty; the other is real options "in" projects, which designs flexibility into technical systems. Section 2.5 reviews the domain literature on decision making in petroleum projects under uncertainty. After the literature review, the research opportunity and contributions for this thesis are identified in Section 2.6: As a summary, the main contributions of this thesis are:

- First, this thesis develops a 4-step generic process and a simulation framework to explore flexible strategies using screening models under multi-domain uncertainty, which fills a research gap in engineering systems design. In contrast to the extensive literature on real options "on" projects (e.g., Trigeorgis, 2002; Copeland and Antikarov, 2003) which focuses on managerial flexibility valuation under market uncertainty using financial option models, this research addresses design flexibility in engineering systems using screening models. This thesis further advances the emergent body of research of real options "in" projects (e.g., Lund, 2000; Zhao and Tseng, 2003; de Weck *et al.*, 2004; Wang and de Neufville, 2006).

- Secondly, the proposed generic process and framework are applied to offshore petroleum projects. An integrated screening model is developed to interconnect the three sub domains of petroleum projects (i.e., reservoir, facility design, and project economic evaluation) at a mid-fidelity level. This thesis develops stochastic models to simulate multi-domain uncertainty (i.e., reservoir, facility, and market uncertainty). A stochastic reserve evolution model is developed as an original contribution to simulate human perception of reserve evolution distinct from the true underlying reserves. Three levels of flexibility (e.g., tieback flexibility, capacity expansion flexibility, and operational flexibility) in oil field development are identified and modeled. This research fills a research gap in the domain of petroleum field development planning. The existing literature on petroleum field development planning primarily focuses on design optimization under single-domain uncertainty using high-fidelity models, while this research focuses on flexible design under multi-domain uncertainty using mid-fidelity screening models. The overall approach is demonstrated through two case studies for the development planning of a large monolithic oilfield and development of a multi-reservoir basin in deepwater.
- Thirdly, the computation framework allows system architects to compare strategies in terms of Value-at-Risk-Gain (VARG) curves, and quantify the Value of Flexibility (VOF) using a Design of Experiments (DOE) approach. Flexibility in design can improve a project's ENPV by reducing downside risks and extending upside gains. This thesis identifies and evaluates three levels of flexibility (i.e., strategic level, tactic level, operational level) in engineering systems. Thus, this thesis provides a generic procedure for developing a computational laboratory to experiment with and explore different strategies during a project's early stages.

Figure 9 shows the identified research gap – using a flexible approach to explore a set of strategies under multi-domain uncertainty. The details will be illustrated in Section 2.6 after the literature review.

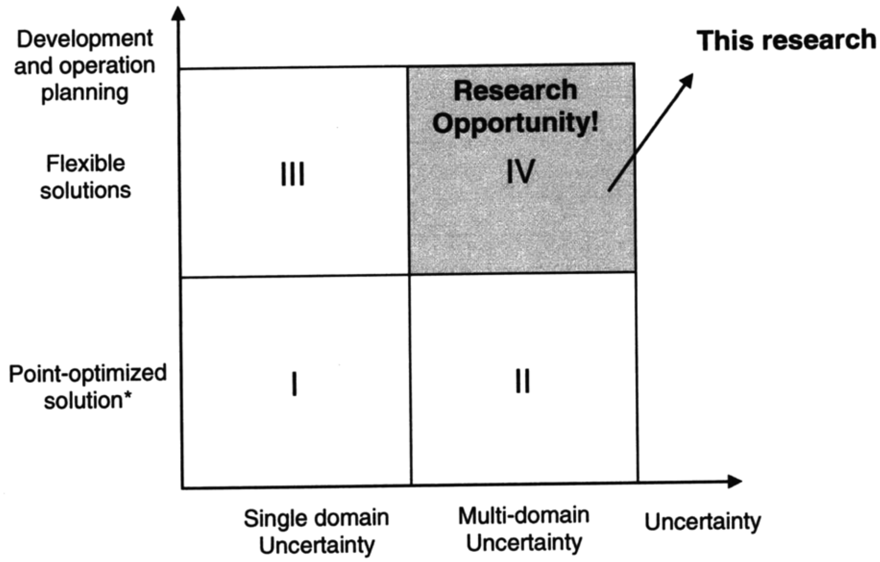


**Figure 9:** Identified research opportunity
(* no change in configuration after initial fielding)

## 2.2 Integrated Systems modeling

Integrated system models interconnect the sub-domain models of resource systems, technical systems design, and project economics evaluation. Such integrated system models are usually developed for architectural analysis and preliminary economic evaluation. Literature on integrated systems modeling can be found in different application domains:

- Manufacturing systems:
  - de Weck (2006) developed a generic integrated product modeling framework for manufacturing firms and applies this framework to optimize the value of an automobile family by using a product platform strategy. In Figure 10, customers and market demand are resource systems, while product architecture and engineering designs are technical systems, and manufacturing cost and investment finance capture the project economics. This modeling framework is an end-to-end representation of typical manufacturing systems.

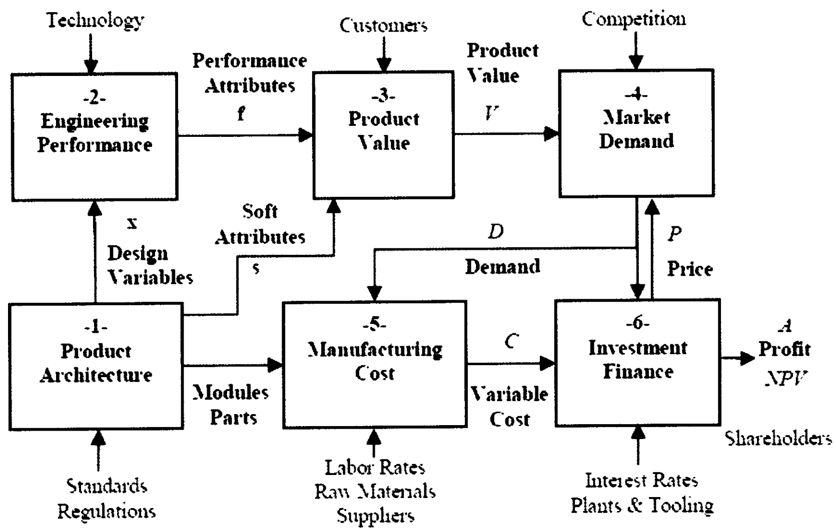


**Figure 10:** Product modeling framework for manufacturing firms
(Figure is adapted from de Weck, 2006)

- Suh et al. (2007) develop a flexible product platform framework and design processes under market uncertainty. The flexible platform design process (FPDP) integrates market segmentation, demand uncertainty, platform design, cost modeling, flexibility in design, and project NPV evaluation. This is another example of using integrated technical-economic models for decision making in flexible manufacturing systems.

- Commercial aircraft design: Markish and Willcox (2003) develop aircraft program level design and evaluation tools to measure the value of a new family of aircraft. The integrated model combines the aircraft design and performance models, the aircraft manufacture and lifecycle cost models, and the airlines' revenue model. A dynamic programming approach has been applied to simulate real-time decision making as market uncertainty is resolved over time
- Communication satellite systems: de Weck *et al.* (2004) develop a flexible architecture evaluation framework for Low Earth Orbit (LEO) constellations of communication satellites. The proposed framework integrates a stochastic customer demand model, the satellite architecture design, a lifecycle cost model, and a program economics evaluation. The integrated flexibility valuation framework is applied to analyze the value of flexible staged development of the communication satellite systems, as compared to a rigid all-in-one design.

- Satellite fleet: Hassan et al. (2005) develop an architecting framework which integrates spacecraft engineering design with an economic analysis to maximize the financial value of a fleet to the operator under market uncertainty. Figure 11 is adapted from this paper. The framework couples the economic and technical domains. The economic domain includes a forecast of market demand for satellite services, which are uncertain and dynamic, and the ROV model, which evaluates the Net Present Value (NPV) of a fleet under uncertainty and constructs the Value-at-Risk (VAR) curve for each architecture. The technical domain includes spacecraft (S/C) sizing and reliability models that are coupled with a heuristic optimization approach (Genetic Algorithm (GA)).

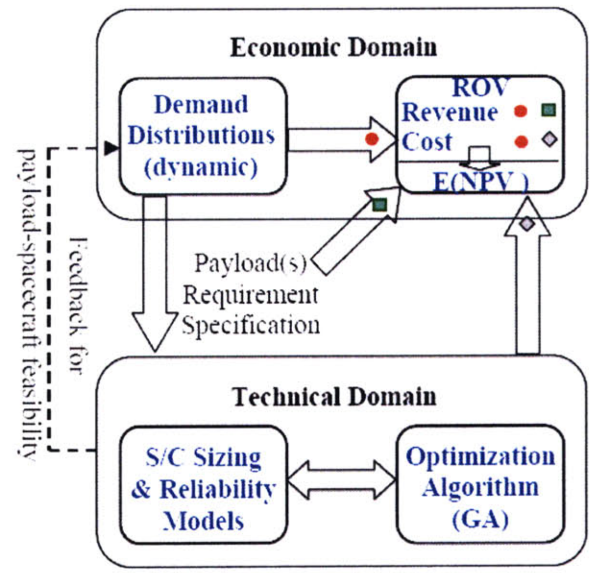


**Figure 11:** Satellite fleet architecting framework
(Figure is adapted from Hassan *et al.*, 2005)

- Petroleum projects: Lund (2000) developed a stochastic dynamic programming model for development planning of offshore petroleum projects. The main components for the optimization model include a simple representation of reservoir production ("tank model"), facility capital and operating cost inputs, and a project economic model. This paper discusses different types of flexibility (e.g., flexibility to drill exploration wells, flexibility to expand platform capacity) and multi-domain uncertainty (i.e., reservoir volume, crude oil price). This paper is one of the closest relevant papers to this thesis. However, this paper has the following limitations: First, the sub domains are not modeled at a similar level of detail. For example, there is no facility model, and CAPEX and

OPEX for different development scenarios are assumed as fixed inputs. Thus, this model cannot capture the dynamic coupling between reservoirs and facilities. Secondly, reservoir uncertainty is simplified as three discrete values (High-Low-Mean). This paper also doesn't make a distinction between true reservoir volume and the evolution of human perception of the value on which decisions are based. Thirdly, this paper doesn't model architectural complexity and flexibility, such as evolving configurations for multiple facilities and reservoirs in a hydrocarbon basin. The case study shown in this paper only considers the single reservoir and single facility. This thesis is built on Lund's work to some extent, addresses all these identified limitations, and develops a screening model and simulation framework to explore different types of flexibility for petroleum projects.

- Offshore gas field development planning: Goel and Grossmann (2004) developed a stochastic programming approach for planning of offshore gas field developments under reserves uncertainty. The stochastic programming model includes decisions on the locations of wells and production platforms and development timing, uncertainty in size and initial deliverability of a field, project cost and NPV calculation. It assumes a linear model for reservoir production.
- Water resource systems: Wang and de Neufville (2006) developed a two-staged process – a screening model and a simulation model -- to screen out and then evaluate real options "in" water resource systems. The screening model is a simplified, conceptual, low-fidelity representation of the system, which includes key uncertain parameters, design variables, and a revenue model. The simulation model involves a detailed stochastic model of the water resource systems and is used to refine the designs identified by the screening model.

Although the selected literature on integrated systems modeling comes from various domains, generally they include three sub-domains: namely, the resource domain, the technical domain and the economic domain. Table 2 shows the list of these three domains for the selected papers. The resource domain could be consumer/market demand, or natural resources, such as hydrocarbon reservoirs or water resources. The technical domain involves the design of technical systems including facilities to transform elements from the resource domain into the economic domain to generate value. The economic domain mainly refers to the financial outcomes (i.e., cost of capital, revenue, net profit) of the system and quantifies value. As demonstrated in the literature, integrated system modeling means to fully interconnect these three domains. Figure 12 shows a generic integrated screening model. There are three key sub systems: the input/resource system, production systems, and output systems. These three sub systems are interconnected by feed forward and feedback flows. The model intends to capture the internal dynamics of these subsystems and their interactions at a mid-fidelity level. Chapter 4 will further develop and instantiate this generic model for petroleum systems.

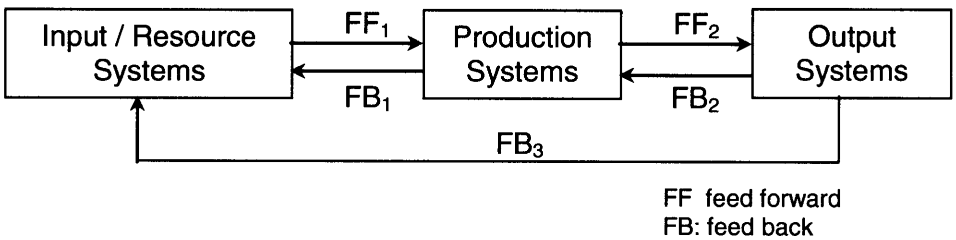


**Figure 12:** A generic integrated screening model

**Table 2:** Three domains for integrated system models

| | Applications | Resource domain (inputs) | Technical domain ("transformer") | Economic domain (outputs) |
|---|---|---|---|---|
| **de Weck (2006)** | Automotive | Consumer /market demand | Product architecture design | Manufacturing cost and project NPV |
| **Suh et al. (2007)** | Cars | Consumer/ market demand | Flexible product platform | Cost model and project NPV |
| **Markish and Willcox (2003)** | Aircraft | Demand for air transportation | Aircraft design and performance models | Lifecycle cost model, revenue model, project NPV |
| **de Weck et al. (2004)** | Satellite | Consumer/ market demand | Flexible architecture for communication satellites | Lifecycle cost (LCC) model |
| **Hassan et al. (2005)** | Satellite | Demand for satellite service | Satellite fleet architecture, satellite sizing and reliability model | Cost and revenue models, Project NPV |

| | | | | |
|---|---|---|---|---|
| **Lund (2001)** | Oil and Gas | Hydrocarbon reservoirs, reservoir production model ("tank" model ) | Hydrocarbon exploration production systems (well, platform) | Market uncertainty model, CAPEX and operating cost inputs, Project NPV |
| **Goel and Grossmann (2004)** | Oil and Gas | Gas reservoirs (linear reservoir model with size and initial deliverability uncertainties) | Hydrocarbon production systems (well and production platforms, wells, flowlines) | Cost and project NPV |
| **Wang and de Neufville (2006)** | Water Resources | Water resource in a river basin (stochastic waterflow) | Electrical power plant (selection of locations, capacity design) | Cost and revenue models |

**Stratified Strategy for Systems Modeling**

For integrated system modeling for capital-intensive engineering systems, there are two approaches to handle modeling complexity:

- One step modeling approach: Using either low-fidelity models or high-fidelity models for technical and business decision making. Examples of using low-fidelity models can be found in operations research (e.g., linear, nonlinear, or stochastic programming). Using high-fidelity models for business decision making is widely used in industry, such as the petroleum industry (high degree of fidelity but low degree of integration), aerospace industry (high fidelity and high degree of integration).
- Two-step modeling approach: This a stratified strategy: First, low or mid-fidelity models are used as screening models to explore critical variables and identify promising strategies or designs during a project's conceptual design stage, and then high-fidelity models are applied to verify and evaluate the designs during the detailed design stage. Wang and de Neufville (2006) propose a two-step procedure for design flexibility in water resource systems.

How to choose among these two approaches depends on the nature of the problem. Figure 13 shows the typology for the modeling approaches. Depending on the level of uncertainty and complexity, we can classify four quadrants. Along the vertical axis, if the level of complexity is low, the one step modeling approach (using either low or high-fidelity models) is usually sufficient to deal with the modeling complexity; if the level of complexity is high and there are complex interactions among multiple sub-domains/disciplines, a stratified two-step modeling approach is perhaps more appropriate. Along the horizontal axis, if the number of uncertain variables is small and the volatility is low, optimization-based approaches can be applied to search for point-optimal solutions that perform best when uncertain variables vary within small ranges; if uncertainty is high, the point-optimal solutions can lead to lock-in (Silver *et al.,* 2005), and the flexible approach is more appropriate. The flexible solutions can adapt to future uncertainty. A petroleum project is a type of problem with both a high degree of uncertainty and complexity, thus, we apply the two-step modeling approach with a focus on flexibility in design. However, this thesis focuses only on the first step in the two-step approach – using mid-fidelity screening models to explore promising strategies or designs.

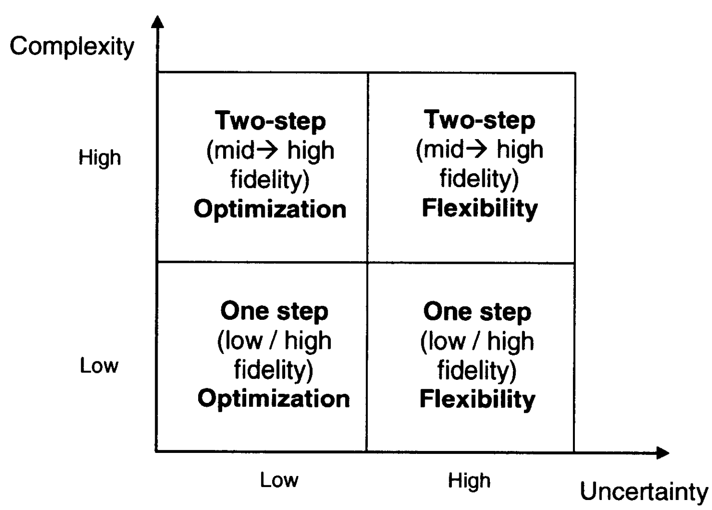


**Figure 13**: Typology of modeling approach

## 2.3 Uncertainty in Engineering Systems

Engineering Systems is a new multidisciplinary field of study of complex socio-technical systems. It extends traditional engineering sciences from technical systems to social, economic, and management domains.

Moses (2004) discusses foundational issues associated with large-scale, complex engineering systems, such as architecture, uncertainty, flexibility, robustness, safety, and sustainability. Moses argues that Engineering Systems emphasizes non-traditional properties or goals of systems, often called "ilities", such as flexibility, robustness, scalability, safety, durability, sustainability, and reliability. Among these foundational issues and "ilities," uncertainty and flexibility are closely related to the theme of this thesis – exploring flexibility under uncertainty. Moses explains the relationship between uncertainty and flexibility as follows, "*Managing the evolution of systems in an uncertain world is a key goal of Engineering Systems. Predicting the uncertain future is difficult, but to the extent that one can use past events as a guide to designing flexibility alternatives or options into a system, the cost of adapting to similar events in the future will be greatly reduced. Viewing uncertainty as an opportunity differentiates Engineering Systems from traditional engineering that is often concerned with reducing risk.*"

The notion of managing uncertainty by designing flexibility into Engineering Systems is further framed by de Neufville *et al.* (2004). This paper discusses uncertainty management as a significant long-term foundational issue for planning, design, and management of Engineering Systems. This paper contrasts traditional engineering design and risk management approaches with the engineering systems design approach. This paper says "*The traditional pattern in engineering is to design to specifications set outside the engineering process, as by client wishes, design codes or governmental regulations. The traditional engineering task is to optimize the technology so that it meets a set of criteria.*" de Neufville *et al.* (2004) further explain: "*Designing for uncertainty changes this approach. It requires us to examine scenarios in which competitive forces, shifts in customer preferences, and political events change the definition of effective design.... Going beyond the more usual passive response to risks, it brings in an active approach to both design of engineering products and of the economic and regulatory environment that surround engineering systems. Furthermore, it gives weight to the upside opportunities associated with uncertainty, in addition to the traditional concern with downside losses and risks.*"

Uncertainty management is a very critical issue for design, development planning, and operation of engineering systems. Due to complexity of engineering systems, it is not a straightforward process to identify critical uncertain factors which impact systems design most. There is a new stream of literature discussing uncertainty and its management strategies in complex engineering systems:

de Neufville *et al.* (2004) developed a two-way topology for managing uncertainty in Engineering Systems by combining the possible time scales and modes of response. Table 3 shows this two-way typology for managing uncertainty in Engineering Systems Design. Examples of manufacturing systems are given in the table. There are three time scales -- operational, tactical and strategic-- to manage uncertainty ranging from nearest term to longest. Operational decisions concern immediate issues (days/weeks). Tactics refers to decisions that take place over a middle-range time scale (months or a few years). Strategy deals with long-term issues (lifecycles of systems, over many years or decades). There are at least three basic ways to manage uncertainty. One can either reduce uncertainty itself, or enable the system to respond to it passively or actively. Passive management of uncertainty does not require modifying systems' configurations and operations. Robust design is one example of a passive approach to managing uncertainty by designing systems in such a way that they can deliver target performance under a variety of circumstances (e.g., noise factors). Active management of uncertainty is to intentionally design flexibility into systems which gives the systems the ability to adapt to future uncertainty. The next section will give a detailed literature review of flexibility and its analytical approach – real options analysis.

**Table 3**: Two-Way Typology to Manage Uncertainty in Engineering Systems Design for Manufacturing Systems (Table adapted from de Neufville *et al.*, 2004, courtesy of Dan Frey)

| Time Scale and Mode of Response | Uncertainty Management (direct reduce / management uncertainty) | System Modification | |
|---|---|---|---|
| | | Passive: Robustness | Active: Flexibility |
| Operational | Correcting a new source of variation revealed by statistical process control | Increasing a machine tool's stiffness so to avoid chatter and thereby improve surface finish | Design a machine to detect chatter and change feed rate automatically to avoid poor surface finish |
| Tactical | Investing in a system to control manufacturing process parameters, like temperature, pressure, and humidity | Robust parameter design – selecting levels of processing parameters that ensure adequate performance over a wider range of conditions | Organizing a plant (e.g., into cells) so that it can adapt to month-to-month changes in product mix. |
| Strategic | Implementing a system (e.g., six sigma) by which you work with your employees and suppliers to continually improve quality and cost. | Setting up a technology strategy so that your plant can meet the new accuracy demands that are forecast to be needed in ten years | Managing a network of suppliers so that you can add emerging new capabilities and drop suppliers that become uncompetitive |

Hastings and McManus (2004) classified several different types of uncertainty: lack of knowledge, lack of definition, statistically characterized variables, known unknown, and unknown unknowns. The uncertainty due to lack of knowledge and lack of definition can be reduced by spending effort on acquiring more information to clarify the ambiguity. On the other hand, there are uncertainties that are irreducible, in other words only the occurrence of future events will turn these uncertainties into known facts. Hastings and McManus also develop a framework to deal with uncertainty. This framework includes four key concepts: 1) Uncertainties are things that are not known or known only imprecisely. They are value-neutral, and thus can lead to risk or opportunity. 2) Risks are pathologies created by uncertainties. They are often quantified as *(probability of uncertain event)*(severity of consequences)*. Risk has a negative connotation, but uncertainty may also create opportunity. 3) Mitigations are technical approaches to risk minimization while exploitations are efforts to capture and enhance opportunities. 4) Outcomes are attributes of the systems to cope with uncertainty, such as reliability, robustness, versatility, flexibility, evolvability, and interoperability

Building on Hastings and McManus' work, McConnell (2007) distinguishes four types of uncertainty depending on knowledge of likelihoods and knowledge of events: statistically characterized phenomena, known unknowns, overlooked unknowns, and unknown unknowns. To address different types of uncertainty require different approaches. McConnell primarily addresses one type of uncertainty, that of statistically characterized phenomena, through a life-cycle flexibility framework. Figure 13 shows the four types of uncertainty organized around knowledge of events and event occurrence probabilities. For statistically characterized phenomena, both uncertainty surrounding possible events and their accompanying probabilities are well known. For known unknowns, the occurrences of the events are known but their probabilities are not known. For overlooked unknowns, events would have been well defined if they had been considered. For unknown unknowns, events and probabilities are not defined or could not be defined at all a priori. Once an event occurs, it is no longer an unknown unknown, and may reveal an entire new class of considerations to be taken into account into the future.

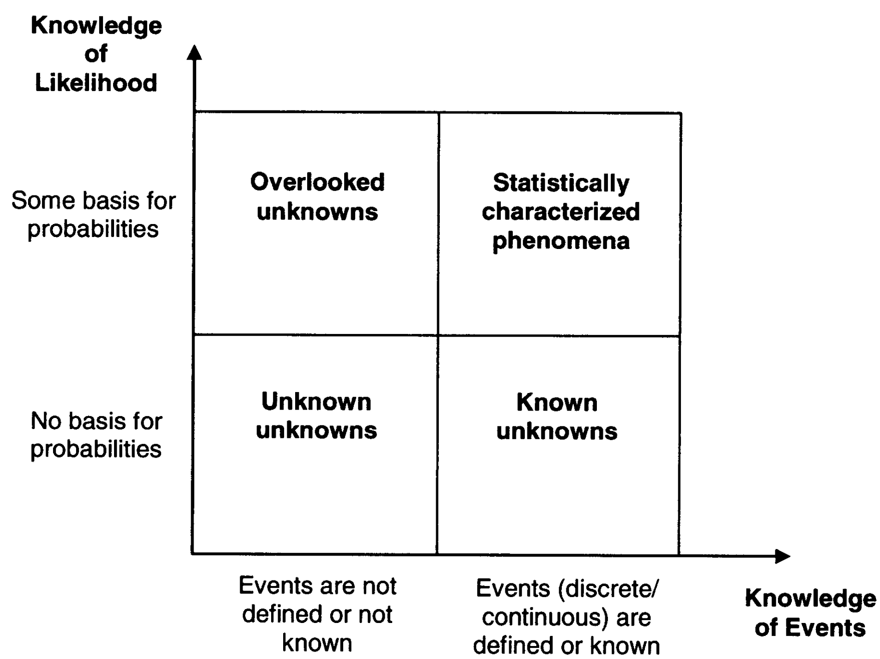


**Figure 14:** Four types of uncertainty
(Figure is according to Hastings and McManus, 2004; McConnell, 2007)

de Weck *et al.* (2007) provide a classification of uncertainty for early product and system design. Figure 15 shows the sources of uncertainty and their contexts. Uncertainties within the typical system boundary (shown as a dashed box in Figure 15) can be influenced by the system designers or firms to a greater extent. Uncertainties within the system boundary fall into the category of endogenous (or internal) uncertainty, which generally includes product and corporate contexts. Uncertainties outside the system boundary can be influenced by the designers or firms to a lesser extent, and they fall into the category of exogenous (external) uncertainty, which includes user context, market context, and political and cultural context.

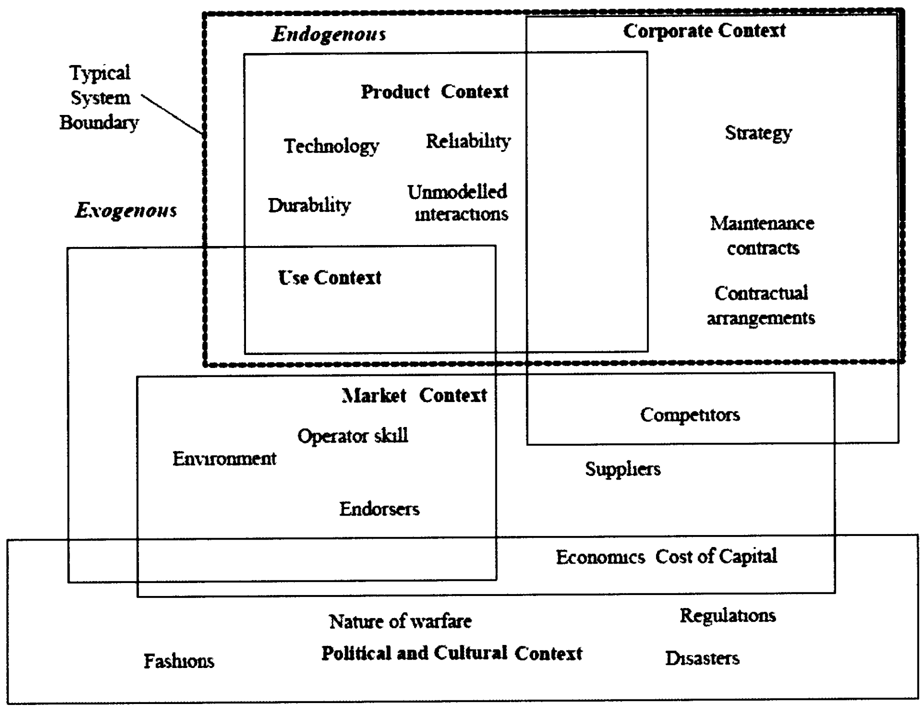


**Figure 15**: Source of uncertainty and their contexts
(Figure is adapted from de Weck *et al.*, 2007)

Thunnissen (2003) gives a literature survey of uncertainty definitions and classifications from various fields ranging from social sciences, to natural sciences, to engineering. Thunnissen proposes an uncertainty classification framework for design and development of complex systems. In this framework, there are four types of uncertainty: ambiguity, epistemic, aleatory, and interaction uncertainty. :

- <u>Ambiguity uncertainty</u> is imprecision due to vague definitions and communication. Although it can be reduced by linguistic conventions and careful definitions, ambiguity remains an unavoidable aspect of human discourse. However, sometimes ambiguity is deliberately maintained or upheld (e.g., in a contract) to retain the freedom to interpret language in different ways.

- Epistemic uncertainty is any lack of knowledge or information in any phase or activity of the modeling process. In the literature, epistemic uncertainty also goes by the names: reducible uncertainty, subjective uncertainty, model form uncertainty, state of knowledge, and type B uncertainty. Epistemic uncertainty can be further classified into model, phenomenological, and behavioral uncertainty.
- Aleatory uncertainty is inherent variation associated with a physical system or environment under consideration. Aleatory uncertainty has several other names: irreducible uncertainty, inherent uncertainty, noise, type A uncertainty. A decision-maker (such as an engineer or designer) has little control over aleatory uncertainty in the design and development of complex systems.
- Interaction uncertainty arises from unanticipated interaction of many events and/or disciplines, each of which might, in principle, be foreseeable. Potential techniques to deal with this type of uncertainty are simulation, multidisciplinary design optimization (MDO), and complexity science.

The classification of various uncertainties is an integral part of ongoing research on managing and mitigating the effect of all types of uncertainty in the design and development of complex multi-disciplinary engineering systems. This thesis addresses the last three types of uncertainty as proposed by Thunnissen (2003): type B uncertainty, type A uncertainty, and interaction uncertainty in complex engineering systems. For example, in petroleum projects, reservoir uncertainty is type B uncertainty which can be reduced by acquiring more information. However, the speed of uncertainty reduction depends on learning processes as well as potential unexpected events, such as sudden discovery of fault structures in a reservoir. Market uncertainty for hydrocarbon product prices is type A uncertainty, which is irreducible as the prices for hydrocarbon products are continuously evolving into the future. Facility uncertainty (such as offshore oil platform production availability) is interaction uncertainty, which depends on interactions between project schedules, metrological events, reservoir conditions, etc. In this thesis, each type of uncertainty has its own uncertainty propagation model. This thesis proposes and demonstrates a simulation framework to take into account all these three types of uncertainty.

**Summary for Section 2.3:**

In summary, uncertainty has been recognized as an important issue for the design and development of complex engineering systems. Different types of uncertainty require different management approaches. For example, design flexibility and robust design are appropriate for epistemic uncertainty; direct uncertainty management (i.e., reducing uncertainty in the systems) is appropriate for aleatory uncertainty; simulation-type approach (e.g., Monte Carlo simulation for interaction uncertainty) would be appropriate for interaction uncertainty among multiple disciplines. When faced with uncertainties in complex engineering systems, decision makers or system architects need to take a holistic view of the problem.

Table 6 shows the taxonomy for uncertainty in this thesis. Examples for petroleum projects are given in the table. We identify three types of uncertainty in engineering systems, namely technical uncertainty, market uncertainty, and socio-economic-political uncertainty. Technical uncertainty is endogenous uncertainty while market and socio-economic-political uncertainty are exogenous uncertainties. In this thesis, socio-economic-political uncertainty is not considered and modeled. Using petroleum projects as an example, technical uncertainty includes subsurface (e.g., reservoir) and surface (e.g., facility) uncertainty. Reservoir uncertainty is reducible uncertainty because the characteristics of a reservoir are static values (on the timescale of the project) and they have evolved into a quasi steady state over millions of years. Decision makers can improve their understanding of reservoirs by investing on acquiring more information, such as drilling more exploration/appraisal wells and conducting seismic surveys. Facility uncertainty is irreducible because it includes the random events (e.g., systems' failures) and other possible significant events (e.g., facility shutdown due to hurricanes or natural disasters). Market uncertainty, such as the crude oil price, continuously evolves into the future and it can not be resolved ahead of time, thus, market uncertainty is an irreducible uncertainty. This thesis develops stochastic models for the reservoir, facility and market uncertainty, and the simulation framework concurrently takes into account all these three types of uncertainty in petroleum projects.

**Table 4:** Taxonomy for uncertainty in this thesis

| | Technical Uncertainty (Endogenous) | | Market Uncertainty (e.g., crude oil price) (Exogenous) | Socio-economic-political Uncertainty (**NOT** considered in this thesis) (Exogenous) |
|---|---|---|---|---|
| | Reservoir (Subsurface) | Facility (Surface) | | |
| Nature of uncertainty | Reducible | Irreducible for facility availability uncertainty (e.g., shut down due to hurricanes)<br>Others may be reducible during development | Irreducible | |
| Approach (simulation-based) | Simulate human's learning processes on reserve estimates | Simulate facility availability (FA) | Simulate the uncertainty propagation | |
| Model | A reverse Wiener stochastic process model with disruptive jumps (Chapter 3) | A simulation model (with Expected FA, random walks, and probabilistic significant events) for FA (Chapter 3) | Standard Geometric Brownian Motion model and lattice model for crude oil price (Chapter 3) | |

## *2.4 Flexibility in Engineering Systems*

Flexibility is a term which can be found in many disciplines, such as engineering and management. There are many different definitions for flexibility among these disciplines or even within a discipline. Saleh *et al.* (2007) gives an excellent multi-disciplinary review of flexibility and say that "*flexibility [is] a popular but not academically mature concept…, The concept of flexibility is today where the notion of quality was some 20 years ago, vague and difficult to improve, yet critical to competitiveness.*" This paper reviews the concept of flexibility through multiple disciplines, such as decision theory, real options, manufacturing systems, and engineering systems design:

- <u>Decision theory</u>: Mandelbaum and Buzacott (1990) develop a framework for flexibility in the context of decision theory. They consider a two-period decision problem. Flexibility is defined and measured by the number of options which are still open in the second period after a decision has been made in the first period. More remaining choices indicate a large degree of flexibility.

- Real options: There is an extensive literature in real options addressing managerial flexibility, and it is worth a separate literature review. (We will give a detailed real options literature review in sections 2.4.1 and 2.4.2.) Here we just review the basic concept. The argument within this literature goes as follows: today's markets are often characterized as hypercompetitive. Uncertainty and volatility are the main attributes of such markets in which important information needed to make investment decisions is either unknown or known to change with limited predictability. The best course of action, or investment plan, based on current information about market conditions may prove inadequate as the future unfolds. Flexibility is introduced in this context as a managerial way of dealing with market uncertainty. In summary, the real options literature focuses primarily on capturing the financial value of managerial flexibility (e.g., flexibility of postponing an investment decision). Its applicability to engineering design flexibility has recently been proposed and demonstrated (de Weck *et al.* 2004; Wang and de Neufville 2006). This new stream of literature is also called "real options 'in' projects," which is treated as flexibility in design in this thesis.
- Manufacturing systems: Research on flexibility in manufacturing systems has grown dramatically since the 1980s. The major focus of the literature is on defining and classifying different types of flexibility for manufacturing systems (e.g., Browne *et al.* 1984; Sethi and Sethi 1990), developing optimization algorithms for designing manufacturing systems with flexible capacity under demand uncertainty (e.g., Cooprider, 1989; Fine and Freund, 1990) and for flexible assembly system designs (e.g., Graves and Holmes-Redfield, 1988), and discussing manufacturing flexibility as a strategy to proactively respond to uncertain environments and to improve a manufacturing firm's competiveness (Gerwin, 1993). Flexibility is generally accepted to be an attribute of a manufacturing system that is capable of changing in order to deal with uncertainty and a changing environment (Sethi and Sethi 1990). Flexibility thus implies an ability to reconfigure manufacturing systems in order to effectively respond to changes in customer requirements, technical advancement, market conditions, etc. Since different uncertainties

around manufacturing systems exist, different types of flexibility have been identified in the literature.

- Volume flexibility is defined in relation to uncertainty in the level of demand for a product, and is considered to be the ability of the systems to accommodate the changing volume for a given part while remaining cost competitive (e.g., flexible assembly lines).
- Routing flexibility is defined as the ability to produce parts/products through different sequences of operations, or by alternative routes through the manufacturing systems.
- Expansion flexibility is defined as the ease with which production capacity can be increased.
- Product mix flexibility is defined as the ability to manufacture a variety of products without major modification of existing facilities.
- Platform flexibility is defined as the ability to share common elements or processes to satisfy the needs from multiple market segments. Research on flexible product platforms addresses the issues of a platform-based product family strategy and design methods to achieve such flexibility (e.g., Suh *et al.* 2007; Volkswagen's group A platform for mid-size automobiles, such as Skoda, Volkswagen, and Audi).

- Flexibility in systems design: In recent years, an emerging literature has proposed to bring the concept of flexibility to the realm of system design. Saleh *et al.* (2008) reviews the literature in this domain and makes a distinction between flexibility in the design process and flexibility of the design itself. Researchers investigating flexibility in the design process have developed various methods for dealing with uncertainty in requirement specifications in the early stages of designs. More recently, a growing body of research (e.g., de Weck *et al.* 2004; Wang and de Neufville 2006) has explored issues of flexibility in system designs. In this context, flexibility is achieved intentionally by design, which not only mitigates downside risks but also allows systems to capture upside opportunities. Even within the field of system design, a variety of definitions for flexibility exists, such as:

- Hastings and McManus (2004) define flexibility as the "*ability of the system to be modified to do jobs not originally included in the requirements definition.*"
- Allen et al. (2001) define flexibility as "*the property of a system that is capable of undergoing changes with relative ease.*"
- Saleh et al. (2003) define flexibility as "*the property of a system that allows it to respond to changes in its initial objectives and requirements – both in terms of capabilities and attributes – occurring after the system has been fielded, i.e., is in operation, in a timely and cost-effective way.*"
- de Neufville (2004) defines flexibility as "*the ability to adjust a design of a system in significant ways that enable the system managers to redirect the enterprise in a way that either avoids downside consequences or exploits upside opportunities.*"

Although these flexibility definitions may appear different, the key idea is consistent: that is, flexibility is a proactive means to enable a system to be easily modified so that it can adapt to future uncertainty, mitigate downside risks, and exploit upside opportunities. The concept of flexibility in systems design is the theme of this thesis. From the literature, we can see that flexibility in design implies making it easy to adapt a system to future conditions, even if these are not predicted exactly or were not included in the initial requirements. Flexibility is a system's property by design. Flexibility can be found and extended throughout a system's lifecycle. Figure 16 illustrates the lifecycle of a complex system. In this model, flexibility is embedded into the system in the early stages (i.e., conceptual and preliminary designs), in order to enable flexibility during a system's production and operation stages. McConnell (2007) develops a Life-Cycle Flexibility (LCF) framework and applies this framework to commercial aircraft manufacturing enterprises and intelligent transportation systems.

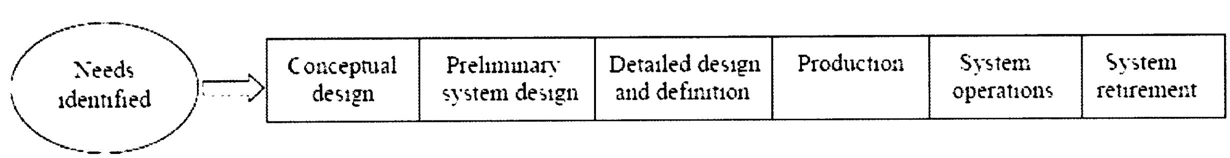


**Figure 16:** Example of a system lifecycle
(Figure is adapted from Saleh *et al.*, 2003)

The words flexibility and robustness are sometimes used interchangeably in the literature or in practice, which causes some confusion. However, flexibility and robustness are separate characteristics of a design. Saleh *et al.* (2008) make a clear distinction between these two terms: *robustness* of a design is the property of a system that allows it to satisfy a *fixed* set of requirements, despite changes in the environment or within the system. In other words, robustness implies de-sensitizing the system's performance or quality characteristics to the system's internal or external changes. *Flexibility* of a design implies an ability to satisfy *changing* requirements. Flexibility is a proactive approach to handle uncertainty, and it enables systems to mitigate downside risks (e.g., start with smaller system initially or reduce the scale of operations) and exploit upside opportunities (e.g., expand systems' scales or their operations when conditions are favorable). In summary, robustness handles changes (uncertainty) without changing system architectures, while flexibility responses to changes (or uncertainty) by actively changing system architectures, designs, or their operations.

There are two ways to have flexibility in a system: one is coincidental flexibility and the other is design flexibility. For the first category, flexibility is not achieved by intentional design; in other words, systems appear to have flexibility without any extra effort in the initial design. For example, the Boeing B-52 bomber has been described as a flexible system because it can be modified easily to accomplish many combat missions, such as close ground support and release of precision munitions, which were not originally envisioned during its design as a strategic bomber. A study (Globalsecurity.org, 2006) shows that the original over-design of B-52's airframe structural subsystem has enabled these flexibilities. But this design of a robust airframe was not planned with the vision to achieve mission flexibility. Hence, this kind of flexibility is called coincidental flexibility. However, design flexibility requires effort from system designers to embed flexibility into the system in the early stages. Examples include development of a parking garage with a stronger foundation to support more floors in the future (de Neufville, 2004), staged development of communication satellite systems -- flexible staged development to cope with market uncertainty (de Weck *et al.*, 2004), and offshore structures building extra structural capacity and deck space for future equipment. For a complex engineering system, it is a very challenging task to identify where and how to embed flexibility in design under multiple sources of uncertainty. This thesis will elaborate and develop an approach: using screening models to identify flexibility under multi-domain uncertainty.

Flexibility has been operationalized with the use of options theory. Financial options theory was originally developed by Black, Scholes, and Merton (Black and Scholes, 1973; Merton, 1973). The work on developing the Black-Scholes model led to their wining the Nobel Prize in 1997. The basic concept of options is defined as the right, but not the obligation, to take some action at a future date at a predetermined price. Options on real assets or projects are called real options, a term first used by Myers in 1977. Real options are built on financial option theory and enable one to evaluate managerial flexibility for project investment. Traditional economic valuation methods for projects, such as Discounted Cash Flow (DCF) and Net Present Value (NPV), estimate a project's future cash flows and discount them to present value. Thus, projects with different time horizons can be compared. However, the DCF-based valuation approach is too rigid, not taking into account managerial flexibility during a project's lifecycle, such as deferment, expansion, and abandonment options. Real Options Analysis (ROA) has been proposed as a new approach for corporate capital budgeting.

Real options can be categorized as those that are either "on" or "in" projects (de Neufville, 2002; Wang, 2005). Real Options "on" projects are financial options taken on technical systems, treating the technology itself as a "black box". Real options "on" projects usually focus on applying various option pricing models to evaluate the value of managerial flexibility (such as postponement, expansion, and termination options) on the projects. However, research on real option "on" projects does not discuss how to design systems in such ways to achieve these managerial flexibilities. For example, real options "on" projects evaluate the value of project expansion flexibility and provide the conditions under which this flexibility should be exercised by making very simple assumptions about the cost of flexibility, but this approach does not give any clue on how to achieve such flexibility in the initial designs. Furthermore, the main uncertainty being considered for real options on projects is a project's exogenous uncertainty such as market uncertainty. On the other hand, real options "in" projects are options created by embedding flexibility into the actual design of technical systems. There is a new and evolving stream of literature on complex engineering systems design and development under uncertainty.

In this type of real options, both technical and market uncertainties have to be considered in order to effectively embed flexibility into designs. In the remainder of this section, literature on these two types of real options will be reviewed.

### 2.4.1 Real Options "on" Projects

Real options "on" projects mainly focus on the financial value of managerial flexibility on the project. This type of flexibility includes deferment, expansion, and abandonment options, etc. A variety of real option valuation techniques have been proposed and developed:

- Analytical solution of Partial Differential Equation (PDE): Using an analytical formula directly solves the partial differential equations and produces one closed form solution. The Black-Scholes equation is the most famous solution. Analytical closed form solutions are mathematical elegant and require almost no computation time or resources. However, unlike the financial options, the parameters for such equations are not always readily apparent, such as the volatility $\sigma$ of a real asset. This approach directly applies option pricing models to evaluate engineering projects without addressing the flexibility in system designs.
- Lattice model: This is a discrete method to represent the stochastic differential equations. The most common one -- recombining the binomial lattice – is a very popular model and is widely applied to real options valuation. The binomial tree model discretizes the time dimension and assumes the underlying asset can move up or down at each time step. Since this model allows recombination of different branches, the number of states only grows linearly with the number of discrete time steps.
- Monte Carlo simulation: This is a very popular and easy to use approach to combining the results of thousands of simulations to represent the stochastic nature of the system response or option value. The main idea of this approach is to use the simulation to evaluate how designs perform as uncertain inputs vary. At the beginning of the simulation, samples are drawn from given distributions, and then a distribution of outcomes can be obtained after simulating many runs. Monte Carlo simulation is suitable for complex systems for which it is either difficult or impossible to obtain analytical formulas for options valuation. Monte Carlo simulation is computationally intensive, generally requiring thousands of runs to obtain a distribution of outcomes.

### 2.4.2 Real Options "in" Projects

In contrast to real options "on" projects, which focus on valuation of managerial flexibility, real options "in" projects are options created by changing the actual design of technical systems. This important distinction was first identified by de Neufville (2002) and then further articulated by Wang and de Neufville (2006). Although the number of papers on real options "in" projects is still very limited, applications have been found in various areas, ranging from small-scale projects (i.e., development of a parking garage) to large-scale infrastructure (i.e., commercial communication satellites, water resource systems, highway development, petroleum production projects). This section selects and reviews several representative papers on real options "in" projects.

- Parking garage: Zhao and Tseng (2003) discuss the value of flexibility in infrastructure expansion by example of a public parking garage development. Enhancing the foundation and columns requires up-front expenditure which enables future expansion flexibility if demand for parking increases. The evolution of parking demand and optimal expansion is modeled by a trinomial lattice and stochastic dynamic programming. A model with flexibility is compared with that without flexibility, and the difference of the optimal value from two models is defined as the value of flexibility. This paper demonstrates that the value of flexibility is significant. de Neufville *et al.* (2006) develop a spreadsheet model for real options analysis of a similar parking garage example. The spreadsheet model is simple and avoids complicated financial options theory. A three-step procedure is developed: (1) optimized base design and NPV without uncertainty; (2) simulated future demand scenarios resulting in a distribution of outcomes (VARG curves for NPV); (3) exploration of various flexibilities, such as capacity expansion options, to shape the distribution of outcomes -- mitigating downside risk and capturing upside potential. This approach illustrates the procedures to evaluate flexibility in design through a very simple example and spreadsheet-based model.
- Satellite systems: de Weck *et al.* (2004) propose a flexible staged deployment strategy for constellations of commercial communication satellites. The approach provides system designers with flexibilities that enable them to match system evolution paths to the actual unfolding demand scenario. A case study demonstrates significant economic benefits of the proposed approach when applied to low earth orbit constellations of communication

satellites. Hassan *et al.* (2005) develop a "Value-at-Risk-Gain (VARG)" approach for evaluating flexibility in complex engineered systems. This paper demonstrates the method through a case study of architecting a flexible fleet of satellites under demand uncertainty for a satellite service in two distinct geographical markets. It shows that the flexible fleet architecture significantly improves the project's outcomes as shown in the VARG curves -- capturing more revenue, mitigating more downside risk, and reducing overall required investment -- compared to those of a traditional, rigid fleet architecture.

- <u>Water resource systems</u>: Wang and de Neufville (2006) propose a procedure to identify real options "in" engineering systems. It consists of a two-step sequential process -- a screening model and a simulation model. The screening model is a simplified, low-fidelity representation of the system which is used to identify key uncertain variables and ranges of flexibilities in the systems. The following simulation model is used to validate critical considerations, such as robustness and reliability of the design. This approach is applied to development of dams and hydropower stations for a river basin.
- <u>Construction or infrastructure projects</u>: Zhao, Sundararajan, and Tseng (2004) present a multistage stochastic model for decision making in highway development, operation, expansion, and rehabilitation. The model incorporates real options in the development and operation phases, and it accounts for the evolution of three uncertainties, namely, traffic demand, land price, and highway deterioration, as well as their interdependences. A simulation algorithm based on Monte Carlo simulation and least-squares regression is developed. Ford, Lander, and Voyer (2002) propose a real options approach for proactively using strategic flexibility to recognize and capture project value hidden in dynamic uncertainties. An example of a proposal for a toll road project demonstrates the proposed method for valuing managerial flexibility. Ho and Liu (2003) present a quantitative valuation method based on modern options pricing theory for evaluating major investments in emerging architecture/engineering/construction technologies. The framework takes into account technology investment risk and embedded managerial options. Ajah and Herder (2005) promote adoption of the real options approach in the conceptual design process of energy and industrial infrastructures, which can offer the designers extra degrees of freedom to systematically consider and design system elements with the ability to react to the technical, economic, and institutional dynamics.

This paper proposes a six-step process for integrating real options into infrastructure design -- (1) establish flexibility needs; (2) identify system uncertainties; (3) determine flexible options; (4) value flexible options; (5) analyze & compare options; (6) integrate the chosen option into design.

- Petroleum Exploration and Production (E&P) projects: Lund (2000) develops a stochastic dynamic programming model for evaluating offshore petroleum projects under uncertainty. Both market risk and reservoir uncertainty are handled by the model. This paper considers different types of flexibility (i.e., capacity expansion flexibility, drilling options). A simulation case study reveals the significant value of flexibility. Particularly, capacity flexibility improves a project's value significantly where uncertainty surrounding the reservoir properties is substantial.

Although these publications have addressed design flexibility in a variety of domains, a coherent and generic framework for identifying and designing real options "in" capital-intensive projects still remains to emerge. For example, uncertainties being considered in the existing literature are primarily exogenous (i.e., market uncertainty, customer demand). For a complex engineered project, there are multi-domain uncertainties (i.e., technical, market, development uncertainties) that can influence the technical or economic success of a project. Furthermore, the literature primarily focuses on particular types of flexibility over a project's lifecycle (i.e., managerial flexibility in projects' early stages, operational flexibility after systems have been fielded). However, a holistic view of uncertainty and flexibility is required to design effective engineering systems under multi-domain uncertainties. Therefore, this thesis intends to narrow this research gap and to develop models and methodologies for identifying and evaluating different types of flexibility over the lifecycle of complex engineering systems under multi-domain uncertainties.

## 2.5 Offshore Petroleum Exploration and Production Projects

### 2.5.1 Background

Offshore petroleum E&P projects are capital-intensive investments under uncertainty. The whole lifecycle of offshore E&P projects can easily span several decades from initial field exploration to abandonment. A generic lifecycle process of petroleum projects is illustrated in Figure 17.

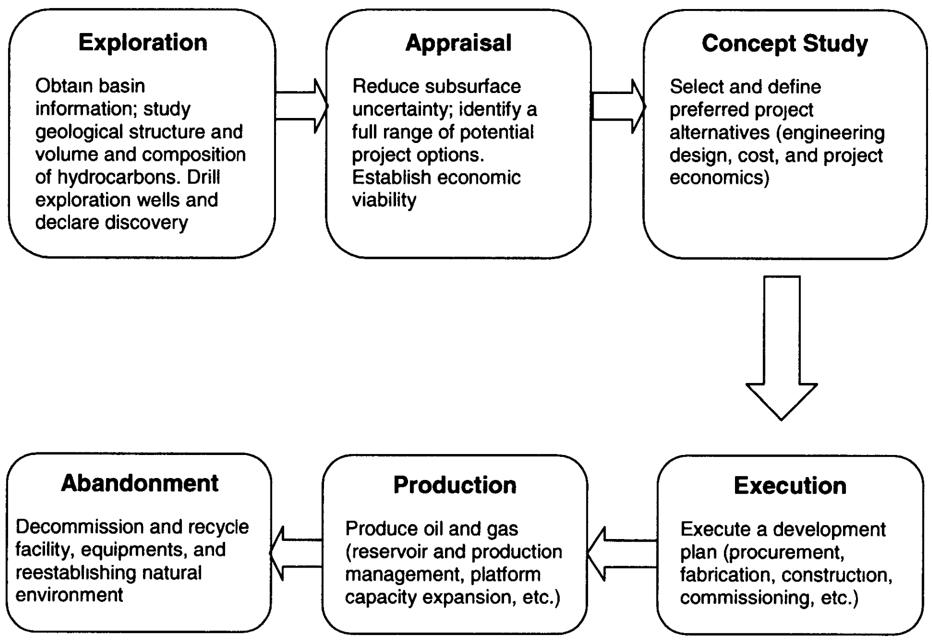


**Figure 17** Lifecycle for an offshore petroleum exploration and production project

During the exploration phase, the main task is to acquire geological information from a basin to understand its geological structure and then to determine the existence of recoverable hydrocarbons underground. Seismic surveys are applied to construct images of geological structures. Other direct samples, such as rock and fluids examples from other discoveries and geological analogues, can provide information about a basin's geological structures and potential fluid properties. All this information can help geologists, geophysicists, and reservoir engineers to infer the existence of hydrocarbons in the basin. Once a structure is identified with potential hydrocarbons, exploration wells are planned and executed. Exploration wells only can identify a hydrocarbon discovery and an appraisal program is required often comprising additional seismic acquisition and appraisal wells to better understand the size of and developability of the discovery. However, getting information from a basin is expensive, especially if the basin is in deep water or severe environmental conditions exist. Only very limited samples are available from exploration wells due to their expense if at all. Hence, the estimates of geological structures and fluid properties are uncertain. Major decisions in exploration involve: whether or not to move to the next stage (e.g., appraisal) given the exploration results; whether or not to continue exploration elsewhere in the basin if results are not promising. The exploration stage carries the highest level of uncertainty for a petroleum E&P project. Major international oil companies usually retain a portfolio of exploration interests among many geological regions, and thus the exploration risks can be diversified and managed using a portfolio approach. Even if a discovery is proven to be technically successful, political and economic conditions need to be favorable for commercial development. The exploration and appraisal stages can take several years up to a decade. It is common for an oil company to conduct exploration of a basin and discovery appraisal for several years before determining whether there is any commercial development opportunity.

During the appraisal phase, the major tasks involve reducing sub-surface uncertainties and identifying a range of design and development alternatives and options. During this phase, more information is gathered (i.e., through appraisal well drilling) to provide better estimates of reservoir sizes, locations, fluid composition, and drive mechanism, etc. Among these, the total amount of recoverable hydrocarbons is the most critical uncertain variable for decision makers. The amount of recoverable hydrocarbons determines the scale of field development and facility sizes. Another main task during the appraisal stage is to identify various alternatives to develop a basin/field and conduct technical and economic feasibility studies. The feasibility study involves identifying and evaluating various development concepts, platform substructure concepts (i.e., Steel Piled Jacket (SPJ), Floating Production, Storage and Offloading (FPSO) vessel), locations of platforms, subsea architectures (i.e., wells, trees), pipeline connections, export systems, etc. Each design and development alternative is accompanied by an estimated development cost and schedule. The appraisal gives a complete overview of the constraints, requirements, risks and opportunities for each alternative.

In the concept study phase, the main task is to select a preferred project alternative and develop a Field Development Plan (FDP). During this phase, one design will be selected from a small set of design alternatives. A field development plan will be further defined as "the best" project alternative. The plan is a key document for achieving proper communications. The primary purpose of this plan is to serve as the conceptual project specification for subsurface and surface facilities, and the operational and maintenance philosophy required to support a proposal for the required investments. It should give management and shareholders confidence that all aspects of the project have been identified. In particular, it should include objectives of the development, petroleum engineering data, operating and maintenance principles, description of engineering facilities, cost and manpower estimates, project planning, and budget proposals. Following the FDP, detailed design of the facilities will start.

In the execution phase, a field development plan based on the results of the concept study will be implemented. The main activities in this phase include finalizing engineering designs of facilities, procuring materials, fabricating facilities, installing facilities, commissioning all plants and equipment. The key challenges in this phase are to deliver the project on schedule and on budget. Typically, this work is executed by a group of firms lead by an international oil energy company, (such as BP, Shell, and ExxonMobil), national oil company, and a network of suppliers and service companies.

The production phase commences with the first commercial production of oil and / or gas ("first oil"). From a cash flow point of view, it is a turning point since now cash is generated and can be used to pay back prior investments. Minimizing the time to "first oil" is one of the most important goals of any new project. The production profile for offshore petroleum projects generally can be characterized by three stages as shown in Figure 18. The y-axis refers to thousands of barrels produced per day (mbd) for crude oil.

- Build-up stage: During this stage, newly drilled producers are progressively brought on line. The speed of ramp-up depends on the drilling schedule, the number of pre-drilled wells, capacity of surface facilities, etc. This stage may last from several months to several years depending on a field's development schedule.

- Plateau stage: A constant production rate is maintained as new wells are still brought on stream to replace the declining production of older wells. This period typically lasts 2~5 years for an oil field, but generally lasts longer for a gas field.
- Decline stage: As the reservoir pressure or percentage of oil in the production fluids decreases, production wells exhibit declining oil production. This stage usually is the longest stage and it may take 10 ~15 years depending on a field's characteristics and recovery scheme (i.e., enhanced oil recovery techniques to extend a field's production life).

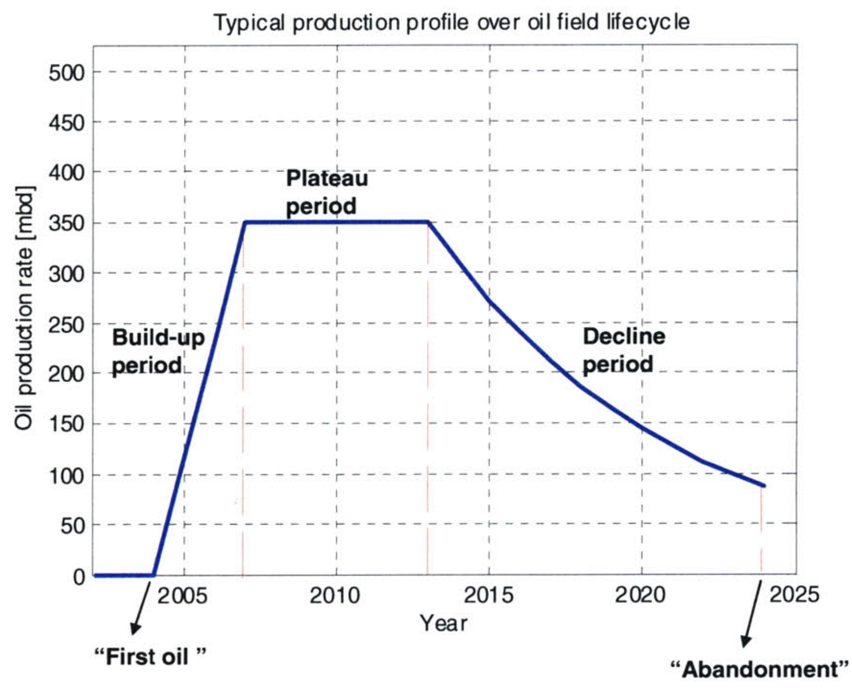


**Figure 18:** A typical production profile for an oil field's lifecycle

At the abandonment stage, field operations will terminate when technical or economic conditions for decommissioning are reached. Towards the end of an oil field's life, the capital spending and asset's depreciation are generally negligible, and thus the economic decommissioning condition can be defined as the gross income being less than the operating expenditures. However, oil companies may have the option to defer the decommissioning by reducing the operating cost (i.e., lease or sell the asset to a lower cost operating company) or by increasing hydrocarbon throughputs through enhanced oil recovery. Abandonment is greatly influenced by prevailing crude and gas market prices. If a facility's operating life is longer than the oil field's life, oil companies can use existing facilities (i.e., platforms, export pipelines) to develop nearby fields, which might not be economical to develop otherwise. These nearby fields are not necessarily owned by oil companies who have the facilities. A service charge will be negotiated for other parties to use their production facilities. Decommissioning offshore facilities needs to be done with minimal environmental effects without incurring excessive cost.

In general, there are five major types of decisions involved during the lifecycle of E&P projects:

- The decision to drill or not to drill exploration wells.
- The decision to perform project appraisal often consists of increased seismic acquisition and analysis or planning additional appraisal wells and studies to establish economic viability.
- The decision of choosing a preferred development plan among many alternatives (a field development plan is defined as platform design, subsea architecture, reservoir recovery scheme, project schedule).
- The decision to change project scope during development and operation phases, such as phasing platform, equipment, tieback fields, etc.
- The decision on how to manage the reservoir and maximize recovery, such as injection schemes, production design capacity, including when to abandon a field.
- The business decision to invest in a project or not.

There are a lot of challenges for capital-intensive project investments under uncertainty. For offshore petroleum projects, these challenges can be summarized as follows:

- Offshore E&P projects have long lifecycles. From field exploration to project abandonment, an offshore E&P project can easily span over several decades. Over such a long period, the external environment (i.e., political environment, market conditions) and technology (e.g., Enhance Oil Recovery (EOR)) will very likely change significantly. So, the early field development plan and decision making have long-term impact on field operations and project economic outcomes.

- Offshore E&P projects carry a significant amount of uncertainty (and therefore risk). In every phase of an E&P project's lifecycle, understanding and managing uncertainties in the subsurface, technology, and market is very critical for decision makers and system designers. During a project's exploration, appraisal, and concept study stages, much effort is spent on quantifying and reducing uncertainties and designing robust and flexible development plans to deal with those remaining uncertainties. During a project's execution and operation stages, the focus shifts to managing uncertainty in reactive or proactive ways (i.e., exercising built-in flexible options, such as adjusting project scope, facility architectures, field operations). The next section will provide a detailed discussion of uncertainties in offshore E&P projects. One of the major motivations for this thesis is to develop a methodology for exploring flexible field development strategies.
- Offshore E&P projects are technology-enabled and capital-intensive investments. As easy to access hydrocarbon resources are depleted, oil companies are forced to explore and produce resources in remote, severe environment and geologically challenging conditions (deep water, arctic areas, tight rock). There are a lot of technology challenges for exploring and producing these resources (i.e., drilling several miles into the seabed in thousands of feet of water depth). Technology for deep-water exploration and production is as sophisticated as space exploration. Furthermore, these projects need an enormous amount of capital investment. For example, each production well can easily cost over a $100 million for deepwater oil fields. Multi-billon dollar investments are often needed before production of hydrocarbons can begin. All these issues pose a big challenge for investment planning under uncertainty. A successful offshore E&P project requires both a technologically feasible and economically viable development plan.
- Offshore E&P projects have large socio-economic impacts. Hydrocarbons are non-renewable energy resources, and currently society is still heavily relying on fossil fuels as energy sources. Every bit of hydrocarbons is a precious resource, so it is the responsibility of both oil companies and local governments to maximize oil and gas production in environmentally friendly and sustainable ways. The development of offshore E&P projects needs to take into account socio-economic impacts on the environment, local people, and economic growth. In the concept study, it may turn out

that the most profitable development plan cannot be executed due to socio-economic considerations.

### 2.5.2 Uncertainties in Oil and Gas Exploration and Production Projects

Petroleum E&P projects are inherently risky investments. Field development decisions usually have to be made in the presence of uncertainty from multiple sources. The early estimation of project economic value (i.e., a project's NPV) depends on the forecast of the future hydrocarbon production from reservoirs, development cost, and sustainable market prices for hydrocarbons. The sources of uncertainty for petroleum E&P projects can be classified into six domains as follows:

- **Subsurface Uncertainty**
  - ***Geological uncertainty***: The geological uncertainty includes hydrocarbon location, shape of reservoirs, fault structures, etc. Given information from a reservoir, there are many possible geological realizations. Geostatistics is a formal discipline to quantify geological uncertainty given limited samples. For deepwater offshore fields, reservoirs lie thousands of feet under water and cannot be directly seen or measured. Techniques have been developed and applied for obtaining information to study and estimate reservoir geological conditions; however, such estimation is usually inaccurate. For example, seismic survey data gives a reasonable indication of geological structures, but the resolution of seismic interpolation usually is much larger than the internal heterogeneities, which may result in missing fault structures in reservoirs. Exploration and appraisal wells only sample very limited locations within a reservoir. The reservoir characteristics (e.g., geological structures, rock properties) between these wells are largely unknown.
  - ***Reservoir uncertainty***: Reservoir uncertainty includes uncertainty in fluid properties, such as Pressure Volume Temperature data (PVT) and relative permeability for oil, gas, and water. A flow simulator simulates and predicts a

reservoir's responses as production and injection occur; however, a flow simulator usually gives a single deterministic response by ignoring the uncertainty in inputs. Given uncertainties in reservoir characteristics, the estimate of hydrocarbon volume in place (i.e., Stock Tank Original Oil In Place (STOIIP)) and recoverable volume (i.e., reserves) are uncertain. The percentage of hydrocarbons which is recoverable from a reservoir is called the Recovery Factor (RF). RF depends on a number of factors, such as permeability of reservoirs, existence of a gas cap or aquifer support, depletion and drive mechanisms, etc. All of these factors are uncertain in a field's development planning phase. In practice, recovery factors are estimated using approximation methods such as the field analogous approach (estimate RF based on similar reservoirs), but each field is unique and the estimation may be very inaccurate.

- **Surface uncertainty:** Surface uncertainty refers to the uncertainty in the wells' and production and export systems' performance, such as wells' and facilities' uptime and spare capacity, and well parameter uncertainties (e.g., productivity, API, THP). Facility uptime is influenced by equipment reliability and durability, quality of maintenance as well as meteorological conditions (e.g., hurricanes).
- **Technology uncertainty:** Technology uncertainty refers to uncertainty in exploration and production technology. For example, for ultra deep water fields or fields in severe environmental conditions (e.g., Arctic), existing technologies may not be capable of exploring and producing the field. The development of such fields may rely on technology advancement, which can be highly uncertain in terms of readiness, timing, and can carry risks to the development performance.
- **Development Uncertainty**
  - ***Cost uncertainty***: Petroleum E&P projects require large amounts of CAPEX for field exploration, appraisal, and development stages. The costs of materials (such as steel) and equipment procurement, engineering design, construction, and services are subject to market demand and supply relations. In recent years, due to high crude oil prices and high demand for energy, an increased number of new offshore projects have been launched. As a result, the oil industry is experiencing significant cost inflation due to imbalance in supply and demand for

materials, drilling equipment, and construction services. A sound development plan needs to take into account development cost uncertainty.

  - ***Schedule uncertainty***: The development of petroleum E&P projects is subject to schedule uncertainty due to changing availability of drilling equipment and services, and construction services, etc. Especially when a number of major projects are executed in parallel, project planning and production schedules are heavily influenced by schedule uncertainty, which can delay first oil or gas and destroy value.
  - ***Contract uncertainty***: Delivering a major petroleum project requires a collective effort of oil companies and their contractors. Nowadays, many activities, such as detailed engineering design, construction services, well drilling and completion, and production services, are conducted by contractors and their subcontractors. As a result, the companies operating a field do not own all the technology or knowledge required for field development. The success of a petroleum project will depend on contract performance. Therefore, management of contract uncertainty becomes a very critical issue for operating companies.

- **Political Uncertainty**: The success of a petroleum project is also greatly influenced by political uncertainty, such as changing taxes, PSA terms, government stability in the developing countries, etc.
- **Market Uncertainty:** *Market price for hydrocarbons*: oil and natural gas are commodities that are traded daily in the global markets. Historical data indicates that the prices for crude oil and natural gas are volatile; more recently, the crude prices experienced a spike (from 2004 to 2008) due to many reasons (such as increased demand, shortage of refinery capacity, geopolitical instability in OPEC, and new demand from Indian and Chinese economies). However, in recent weeks (November, 2008) the price has collapsed back to $50 per barrel from a high of nearly $150 in July 2008. A development that has been precipitated by the recent global financial crisis. The development of petroleum projects is heavily influenced by market uncertainty. For example, oil fields in deepwater, originally perceived as uneconomical to develop, have now become major projects for oil companies, given high oil prices.

Table 5 shows the uncertainty domains and corresponding models for addressing these uncertainties for petroleum projects.

**Table 5**: Uncertainty domains for petroleum projects

| Uncertainty Domain | | Description | Approaches |
|---|---|---|---|
| Subsurface Uncertainty | Geological Uncertainty | • Multiple possible geological realizations<br>• Geological structures (shape, compartments, faults, sealing) | • Geostatistics<br>• Bayesian updates<br>• Geological modeling<br>• Exploration drilling<br>• Seismic survey |
| | Reservoir Uncertainty | • Volume and quality of oil/gas<br>• Recovery factor<br>• Well placement | • Reservoir simulation<br>• Sensitivity analysis<br>• Design of Experiments and Response Surfaces<br>• Derivative tree analysis<br>• Optimization under uncertainty (e.g., stochastic programming) |
| Surface Uncertainty | | • Facility uptime and spare capacity<br>• Well parameters' uncertainty (productivity, API, THP) | • Process modeling and simulation (e.g., P-choke software) |
| Development Uncertainty | | • Development cost<br>• Development schedule<br>• Contract | • Project planning methods<br>• Project risk management<br>• Contracting strategy<br>• Use of natural pace |
| Technology Uncertainty | | • Technology challenges for oilfields in deepwater or severe environmental conditions<br>• Beyond current technology capability requires investment in technology R&D | • Technology Readiness Level (TRL)<br>• Pilot study (e.g., early production systems) |
| Market Uncertainty | | Hydrocarbon commodity price uncertainty | • Monte Carlo simulation<br>• Models for price uncertainty: Geometric Brownian Motion, mean reversion, mean reversion with jump, two-factor models |

In summary, offshore E&P projects are subject to multiple domain uncertainties. A sound development plan has to take into account these uncertainties and provide ways to respond to unfolding uncertainties in the future. However, to the author's knowledge, a coherent and comprehensive approach for field development planning with multi-domain uncertainty has not yet emerged and matured in the literature. A number of papers tackle this problem from specific points of view, such as field development optimization under geological uncertainty. In the next section, selected literature on decision making for petroleum project development is reviewed and discussed.

### 2.5.3 Decision Making in Petroleum Projects under Uncertainty

In the domain of petroleum E&P projects, papers at various conferences and in journals have been presented for a number of years to address decision making under uncertainty. The proposed approaches in the literature can be roughly classified into the following areas:

- Optimization-based approach for field development and operation decisions under technical and (/or) market uncertainties
- Uncertainty quantification and modeling
- Closed-loop reservoir management under uncertainty
- Risk analysis and uncertainty management
- Applications of real options and flexibility to petroleum projects
- Integrated systems modeling for decision making

The discussed literature appears in various sources:

1) Online thesis database from Stanford University's Department of Petroleum Engineering. Among 700 theses, the five most relevant papers were found using key word *uncertainty, flexibility,* and *decision making* in the search engine.
2) Online e-library of the Society of Petroleum Engineers website (http://www.spe.org). This e-library includes over 45,000 technical papers from SPE conferences and journals over the past 50 years. Using combinations of key words, such as *uncertainty, flexibility, real options, decision making, integrated modeling,* and *development planning*, over a hundred papers were found in the database, among which a dozen of the most relevant papers were selected for literature review.

3) A special issue was published in the *Journal of Petroleum Science and Engineering* (Vol. 44, no. 1-2): *Risk Analysis Applied to Petroleum Exploration and Production*. Five papers were selected from this special issue focusing on risk and decision analysis; field appraisal and development, and production forecasts under uncertainty; decision making processes and value of information and flexibility; portfolio management and real options valuation.
4) A Real Options in Petroleum website maintained by Dias M.A.G. (http://www.puc-rio.br/marco.ind/main.html).
5) Other sources such as the annual Delft-Stanford Workshop on Closed-Loop Reservoir Management (2004), etc.

Table 7 selects and compares papers in these five areas, in terms of problem statement, methodology, uncertainty (technical and market uncertainties), decision making, and models and algorithms. From the selected domain literature, the following observations emerge:

- Optimization-based approaches and algorithms (SQP, GA, SA, stochastic programming) have been applied to petroleum fields during exploration and appraisal planning and development stages (e.g., Goodwin, 1998; Goel and Grossmann, 2004) or the production stage (e.g., Wang, 2003; Güyagüler, 2002; da Cruz, 2002). Decisions to be optimized include locations or number of platforms and wells, facilities' sizes, and operations strategies.
- Geological and reservoir uncertainty have been taken into account and modeled for decision making in field development. Multiple geological realizations are simulated to provide a probabilistic view of reservoir characteristics and production scenarios (e.g., da Cruz, 2002; Yeten *et al.,* 2004). Sensitivity analysis and experimental design have been used to identify key uncertain variables and to reduce the number of reservoir simulations (e.g., Ligero *et al.,* 2005; Steagall and Schiozer, 2001). Bayesian analysis has been utilized to update prior distributions of reservoir characteristics given new information from well drilling or production information (e.g., Caumon, 2004; Sarma, 2006; Lund, 2000; Armstrong, 2004).

- In the selected literature review, investment decision making is based on the probabilistic distribution of project economic outcomes, such as NPV. In most of these papers, the economic valuation of the project is a major criterion for optimizing or selecting field development and operations strategies under uncertainty. However, these economic models are rather simple. For example, value is calculated as the sale of hydrocarbons produced minus a lump-sum development cost. Facility cost, operating cost, and the fiscal regime of a project are often not explicitly modeled.
- In the risk analysis literature, market uncertainty has been considered in combination with technical uncertainty (e.g., Edwards, 1994; Zabalza-Mezghani, 2004; Armstrong *et al.,* 2004; Cortazer *et al.,* 2001). However, the central focus of the risk management literature is on how to mitigate project losses if conditions are unfavorable.
- In the real options literature, much attention is still focusing "on" projects' managerial flexibilities and their valuations, such as start, stop, and postponement options at various stages of a project (e.g., Dias, 2004; Lund, 2000; Cortazer *et al.,* 2001).

Embedding flexibility into system design under multi-domain uncertainty still remains an area for further research.

**Table 6:** Comparison of selected papers

| | Engineering Systems | Uncertainty | | Models | Methodology | Flexibility |
|---|---|---|---|---|---|---|
| | | Exogenous | Endogenous | | | |
| **Suh, E., de Weck, O. and Chang, D. (2007)** | Flexible automobile platform | Demand uncertainty (GBM model) | NO | End-to-end platform model (customer demand - function requirements - design variables - cost - revenue) | Flexible product platform process, Monte Carlo simulation | Flexible subsystems /components in BIW platform |
| **de Weck, O., de Neufville, R. and Chaize, M. (2004)** | Communications Satellite Systems | Market uncertainty (Binomial tree) | NO | Technical design vectors for characterizing architectures, Lifecycle cost models | Flexible architecture valuation process: (identifying source of flexibility, generate demand scenarios, minimize architecture paths over lifecycle cost, simulate the "optimal" architectural evolution paths ) | Flexible staged deployment |
| **Hassan, R., de Neufville, R., de Weck, O., Hastingss, D., and McKinnon, D. (2005)** | Satellite fleet architecture | Market uncertainty (forecast demand for two distant geographical markets) | NO | Integrated technical and economic models (Satellite fleet architecting framework) | Value-at-Risk analysis, optimization (Genetic Algorithm) | flexibility "in" the architecture design -- flexible fleet architectures |
| **Wang, T. and de Neufville, R. (2006)** | Water resources systems | fixed cost for reservoir, electricity price | Stochastic waterflow | Screening model and simulation model | Two staged process for identifying real options "in" projects | timing option, flexible design option |

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|---|---|---|---|---|---|---|
| **Kalligeros, K. (2006)** | Offshore oil platforms (FPSOs) | NO | Functional requirements uncertainty | Semi-quantitative sensitivity DSM for platform, Invariant Design Rules (IDR), A simulation-based flexibility valuation algorithm | Two-step methodology for valuing flexibility (screening model, a graphical and simulation-based flexibility valuation approach) | Flexibility in FPSO, program-level flexibility for multiple FPSOs |
| **Silver M. and de Weck O. (2007)** | Heavy lift launch vehicles for NASA's space exploration initiatives | Ten demand scenarios for four time periods | NO | Integrated technical (mission inputs, traffic model, LV define) and cost model (system lifecycle cost model, switching cost model) | Time-Expanded Decision Networks (TDN) | Switching flexibility, flexible architectural and operational paths |
| **Lund, M. (2000)** | Offshore petroleum projects | Market uncertainty (oil price GBM model) | Reservoir volume uncertainty (discrete H-M-L), well rate uncertainty (H-L) | reservoir production model, economics model | Stochastic programming, decision tree analysis, real option "on" project (wait, defer, expansion) | Capacity expansion, drilling exploration well, project start/stop/wait/ |
| **Goel, V. and Grossmann, I. E. (2004)** | Offshore gas field projects | No | Reservoir uncertainty (9 discrete scenarios for reserve volume and initial deliverability) | Linear reservoir model, simple economics model | Stochastic programming | Flexible development timing for multiple well platforms |
| **Dias, M.A.G. (2004)** | Petroleum exploration and production projects | Market uncertainty (oil price GBM model, MRM, MR with Jump) | Reservoir volume uncertainty (triangular or lognormal probability distribution) | A simple "business model" NPV = $qBP - D$ | Monte Carlo Simulation, "Option pricing model" | Real options "on" projects (wait or investment, options on information revelation, optional well) |

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|---|---|---|---|---|---|---|
| **Lin, J. (2008) (this dissertation)** | Petroleum exploration and production projects (multi-field and multi-facility planning) | Market uncertainty (oil price) | Technical uncertainty (i.e., reserve estimation, facility availability) | Integrated mid-fidelity model (reservoir, facility, economics models) | Monte Carlo simulation, Value-at-Risk-Gain, A framework for exploring flexible strategies using integrated models and simulations | Real options "in" projects, flexibility at strategic level, tactical level, and operational level |

**Table 7:** Summary of literature on decision making in petroleum E&P projects under uncertainty

| **Papers** | **Category of paper** | **Problem statement** | **Methodology** | **Uncertainty** | | **Decisions to make** | **Models and Algorithms** |
|---|---|---|---|---|---|---|---|
| | | | | **Technical** | **Market** | | |
| Wang (2003) | Optimization-based approach | Determine the optimal production rates, lift gas rates, and well connections for petroleum field production | A two level programming approach: the upper level masters overall solution process and well connections; the lower level optimizes rate allocation | NO | NO | Well connections, production rates, lift gas rates | Models: commercial reservoir simulator and simulation model for gathering systems. Algorithm: separable programming, SQP |
| Güyagüler (2002) | Optimization-based approach | Determine the best location for new wells under geological/reservoir uncertainty | Propose a hybrid optimization technique based on Genetic Algorithm (GA) and kriging algorithm | Multiple geostatistical realizations; Utility theory to quantify the influence of uncertainties | NO | Location of new wells based on NPV calculation under geological uncertainty | Reservoir simulator for synthetic and real-world fields, Genetic algorithm, Kriging algorithm |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| da Cruz, P. S. (2002) | Optimization-based approach | Reservoir management decision making (i.e., producer placement ) in the presence of geological uncertainty | Propose a FULL (quality map) approach to incorporate geological uncertainty | Geological uncertainty (obtain quality map by average individual realizations) | NO | Number of producers and their locations | Reservoir simulator – ECLIPSE, simple economic functions, Algorithm: L-optimal quality map |
| Yeten et. al (2004) | Optimization-based approach | Determine the optimal performance of smart wells under geological uncertainty | Propose a decision analysis approach to determine whether or not to deploy smart completions under geological uncertainty | Geological uncertainty (utility theory) and reliability of control devices | NO | Whether or not to deploy smart completion for well (based on NPV) | Reservoir simulator, gradient-based optimization algorithm, decision analysis |
| McGill, et. al. (1998) | Optimization-based approach | Development planning of multiple fields with a common infrastructure under subsurface uncertainty | Propose a system level optimization procedure for multiple field development problem | Subsurface uncertainty (reserve, well productivity and deliverability and field compartments) | NO | Number of wells, schedule of drilling, facility design, etc. (based on NPV, IRR) | An integrated model (sub-surface, facility , commercial models), Simulated Annealing |
| Goel and Grossmann (2004) | Optimization-based approach | Optimal investment and operational planning of multiple gas field developments under uncertainty in gas reserves | Proposed a stochastic programming model that incorporates the decision-dependence of the scenario tree | Discrete levels for reserve and initial well deliverability (total 9 combinations) | NO | Binary investment decision variables( i.e., install WP or not), (based on ENPV maximization) | Stochastic programming, decision tree, VARG |
| Caumon et. al (2004) | Uncertainty quantification and modeling | Assessment of uncertainty of a global reservoir parameter during early field | Propose a Bayesian-base workflow to assess the uncertainty about a global uncertainty | Sub-surface uncertainty at parameter level (i.e., NTG ) | NO | The choice of geological scenarios, the location of wells | Bayesian framework |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | exploration and appraisal stages | parameter, such as Net-to-gross ratio (NTG) | | | | |
| Edwards (1994) | Uncertainty quantification and modeling | Production prediction uncertainty and its impact on management of oil and gas uncertainty | Shows that the ability to manage oil and gas commodity price uncertainty is dependent upon the ability to quantify uncertainty in production forecasts and reserve evaluation | Production forecast and reserve uncertainty | Oil and gas commodity price uncertainty | Price hedge decision using financial derivative security (based on production forecast and NPV calculation) | Stochastic economic model, hedging strategies |
| Sarma (2006) | Close-loop reservoir management under uncertainty | Real time reservoir performance prediction and production optimization under uncertainty | Propose a close-loop approach for efficient real time production optimization | Sub-surface uncertainty (Polynomial chaos expansions for uncertainty propagation) | NO | Production control variables(well rates, BHP) for NPV maximization | Adjoint model, Uncertainty propagation model, K-L expansions, Bayesian inversion theory |
| Suslick and Schiozer (2004) | Risk Analysis and Uncertainty Management | Review recent contributions and development of risk analysis applied to petroleum field exploration, development and production | Four areas: (1) Risk and decision analysis;(2) field appraisal and development, and production forecast under uncertainty; (3) Decision making process and value of information and flexibility; (4) Portfolio management and Real Options Valuation | -- | -- | -- | -- |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Zabalza-Mezghani et. al (2004) | Risk Analysis and Uncertainty Management | Uncertainty management from field exploration to development and production | Propose several statistical methods, mainly based on experimental design, to evaluating geological scenarios, comparing ranking impact of uncertainty parameters, etc. | Reservoir static and dynamic uncertainties, modeling uncertainty, geological uncertainty, discrete production scenarios | Economic uncertainties | Identify and rank uncertainty parameters, select relevant parameters for production scheme optimization, economic risk evaluation | Experimental design technique |
| Ligero et. al (2005) | Risk Analysis and Uncertainty Management | Petroleum field decision making process is associated to high risk due to geological, economical and technological uncertainties and high investment. The necessity to speedup the process demands simplification of the process. | Propose a simplification framework based on risk analysis (a seven-step approach) | Three discrete values for each of eight reservoir uncertainty attributes (i.e., permeability, porosity, structural model) | NO | Identify critical uncertainty attributes, combine them to generate a sample of reservoir models (based on NPV calculation) | Sensitivity analysis, experimental design, derivative tree technique, VARG |
| Steagall and Schiozer (2001) | Risk Analysis and Uncertainty Management | Uncertainty analysis in reservoir production forecasts during appraisal and pilot production phases | Propose a decision tree technique to simulate a combination of reservoir uncertainty attributes and their impacts on the economic evaluation of reservoir | Sixteen reservoir uncertain attributes (each with four levels: High, Low, Median, None impacts) | NO | Identify most sensitive uncertain attributes and assess their impact on production forecast and project NPV | Decision tree technique, sensitivity analysis, VARG |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Lund (2000) | Real options and flexibility | Valuing flexibility in offshore petroleum projects | Propose a stochastic dynamic programming model for project evaluation under market and reservoir uncertainties, where emphasis is put on flexibility and its value | Reserve uncertainty (three discrete value, H-M-L, and probabilistic transitions), Well rate uncertainty (H-L) | Oil price uncertainty (GBM model) | project start/stop/wait/ option at different stages, capacity expansion flexibility, drilling exploration well (based on NPV calculation) | Reservoir, facility, economics models, Stochastic dynamic programming, Bayesian update |
| Dias (2004) | Real options and flexibility | Review a set of selected real options models to evaluate investments in petroleum E&P under market and technical uncertainties | Focus on market uncertainty modeling and real options valuation methods applied in petroleum E&P projects | Reservoir volume uncertainty (triangular or lognormal probability distribution) | Oil price uncertainty (GBM model, MRM, MR with Jump) | Options to explore, appraise, develop, expand, abandon; options on information revelation, optional well (Based on NPV) | Simple business model (NPV = qBP – D); Stochastic models for oil price |
| Armstrong et. al (2004) | Real options and flexibility | Incorporating technical uncertainty in real option valuation of oil projects | Develop a methodology based on Bayesian analysis to evaluate the option to acquire more information for field development | Priori and posterior distributions for technical parameters (i.e., STOIIP, water saturation, production rate) | Stochastic oil price | Option to gather information from a production logging tool (PLT) (based on distribution of NPV) | Bayesian updating based on Archimedean theory |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Cortazar et al (2001) | Real options and flexibility | Optimal exploration investments under price and geological-technical uncertainty | Develop a real options model for valuing natural resource exploration investment (e.g., oil or copper) when there is joint price and geological-technical uncertainty. | Technical risk factor G (assume following zero-drift constant volatility Brownian motion) | Collapse price and geological-technical uncertainty into "one factor model" | N stage exploration investment decision (calculate value of exploration project) | N stages exploration investment decision model, one factor model for geological-technical and market uncerainty |
| Saputelli et al. (2008) | Integrated systems modeling for decision making | Using integrated field study to make optimal field development decisions | Integrated Asset Model (IAM) and Dynamic Economic model to manage subsurface, surface, and economic uncertainty, Integrated optimization workflow | Subsurface uncertainty and surface uncertainty (pdfs) | Economic uncertainty (pdfs) | Decisions at reservoir, well, and surface facilities levels | Integrated Asset modeling, optimization, mean-variance plot for NPV |
| Williams et al. (2004) | Integrated systems modeling for decision making | Top-down reservoir modeling: | BP's proprietary Top-Down Reservoir Modeling (TDRM): progressively add details to model for decision making | Reservoir uncertainty | NO | Reservoir depletion plans, well placement, etc. | Monte Carlo simulation, sensitivity analysis |
| Narayanan et al. (2003) | Integrated systems modeling for decision making | Field development decisions based on multi-scenario, interdependent reservoir, well, and facility simulation | Present an integrated system that can assist field development decisions (earth model, development strategy, and economics) | Discrete or continuous uncertainty for reservoir, well, and facilities | Discount rate, CAPEX, OPEX inflations | Well placement, drainage strategies with and without injection, and scheduling | Integrated model (geologic models, well production and schedule models, surface networks, economics), Monte Carlo simulation |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Deguchi Hayashi et al. (2007) | Decision making under uncertainty | The Value of Information (VoI) and Value of Flexibility (VoF) in petroleum field development | Develop a methodology to quantify VoI and VoF under uncertainty based on decision tree technique and Geological Representative Model (GRM) | Uncertainties in geological and flow models (i.e., porosity, fault, permeability) | NO | Minimizing risks to field development, identifying critical reservoir uncertainties in risk mitigation | Derivative tree, decision tree, sensitivity analysis, Geological Representation Model (GRM), risk curve (VARG) |
| Begg et al. (2002) | Decision making under uncertainty, real options | The Value of Flexibility (VoF) in managing uncertainty in oil and gas investment | Proposed VoF as positive mindset around uncertainty, VoF changes focus from risk mitigation to value maximization | OOIP uncertainty, | Oil price uncertainty (mean-reverting model) | Injection flexibility, platform size (medium, large, expandable), production rates under market uncertainty | Decision tree analysis, Expected Monetary Value calculation (EMV) |
| **Lin (2008) This dissertation** | Screening flexibility under uncertainty using screening models | Identify and evaluate flexibility in offshore petroleum projects under multi-domain uncertainty | Developed a four-step process and a simulation framework to screen flexible strategy under multi-domain uncertainty | Reserve evolution model, facility, uncertainty model | GBM model for crude oil and gas prices | Strategic decisions (tieback, staged development), tactical decisions (capacity expansion) operational decisions (ARM) | Monte Carlo simulation, Value-at-Risk-Gain, Screening models |

### 2.5.4 Identified Research Opportunity

Figure 19 shows a typology for development planning under uncertainty. There are four quadrants depending on development planning methods and types of uncertainty. For quadrant I and II, optimization algorithms (e.g., SQP, GA, SA, stochastic programming) are applied for field development planning under single or multi-domain uncertainty. Since full-scale reservoir models are usually computationally expensive, the technical uncertainty is treated as several discrete values each with certain probability instead of full probability distributions. Some simplification methods, such as sensitivity analysis, design of experiment, and derivative tree techniques have been applied to simplify the model and reduce the number of simulations. Quadrant III represents another stream of research, which applies real options on petroleum projects under market uncertainty (e.g., crude oil price). Stochastic models, such as Geometric Brownian Motion (GBM), mean reversion, and mean reversion with jump have been applied to simulate the evolution of hydrocarbon prices. The central focus of this body of literature is valuation of managerial flexibility (such as start, wait, and abandonment options) during the lifecycle of a project. Quadrant IV focuses on flexible solutions under multi-domain uncertainty. In this quadrant, the main effort is to screen out or identify promising flexible solutions from a large design space to cope with multi-domain uncertainty. The major task is how to design flexibility into technical systems as a proactive means to respond to future uncertainty, but the exact valuation of flexibility is not the main concern in the screening phase. To the author's knowledge, very few academic papers tackle this problem. This thesis hypothesizes that designing flexibility into technical systems is one of the key sources for creating value and mitigating risk to oil companies. Therefore, this thesis addresses this research opportunity and develops a generic framework and methodology to screen flexibility strategies under multi-domain uncertainty using an integrated mid-fidelity model.

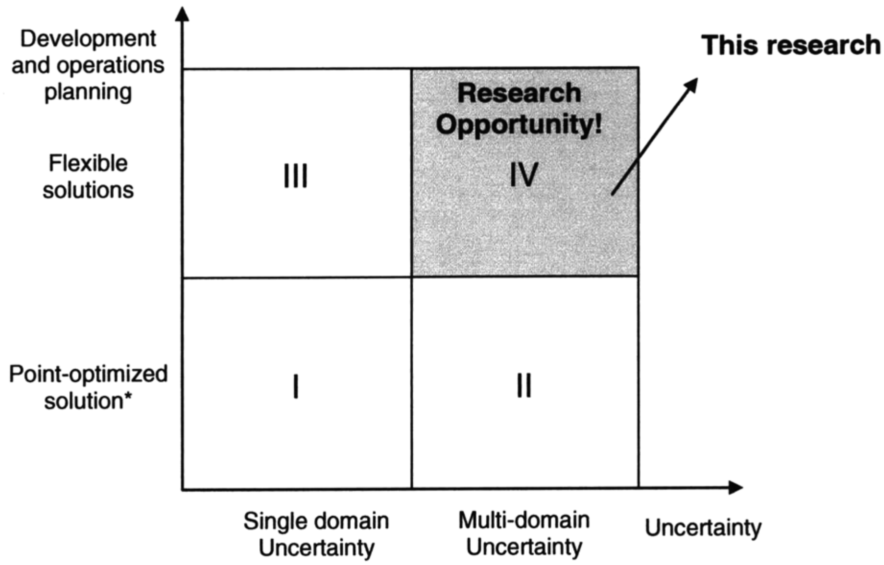


**Figure 19:** Identified research opportunity
(* no change in configuration after initial fielding)

## *2.6 Summary and Contributions*

Table 6 and Table 7 show the streams of literature that have been identified: one is flexibility in engineering systems under uncertainty (6 papers) and the other is domain literature -- decision making under uncertainty in petroleum E&P projects (~20 papers). These two streams of literature provide the most relevant theoretical foundation and application domains for this thesis.

For the first stream of literature, the common theme is to design flexibility into engineering systems such that they can adapt to the future environment. In these papers, technical and economic models have been developed for exploring and identifying flexible systems architectures or strategies, which is followed by detailed engineering design and economic evaluation once promising flexible strategies have been identified. This stratified approach represents a paradigm change from the traditional real options literature (Dias, 2004) -- the focus shifts from valuation of real options (or managerial flexibility) to embedding flexibility into the design of technical systems. Most of these papers focus on system exogenous uncertainty, such as uncertainty in product price and customer demand. Wang and de Neufville (2006) and Kalligeros (2006) slightly touch technical uncertainty, but none of these papers directly address how the evolution of technical uncertainty affects the decisions on flexible systems designs.

Among these papers, Hassan *et al.,* (2005) proposes a simulation-based valuation approach for real options "in" projects -- Value-at-Risk (VAR) analysis, which presents different designs in terms of their cumulative distributions of outcomes.

There are many papers in the second stream of research: decision making under uncertainty for petroleum E&P projects. These papers are selected for literature review since they apply to the same domain. As reviewed earlier, this body of papers addresses key aspects of developing offshore petroleum projects, such as uncertainty quantification and modeling, integrated system modeling for decision making, optimization under uncertainty, and flexibility in field development, etc. But there are several limitations to this stream of literature: 1) In these papers, the models for petroleum project (reservoir model, facility cost model, economics model) are either very detailed and disconnected, or very simple. The cost model is usually given as an input. The interactions between sub-models (i.e., coupled reservoir-facility models) are not well captured. From this perspective, the models shown in these papers are disconnected high or low fidelity models. 2) Technical uncertainty is usually not modeled for decision making processes. For example, the reservoir volume is simply treated as several discrete values (i.e., high-medium-low) with certain probability. Furthermore, none of these papers differentiate between unknown underlying reserves and human perception of this value. The confusion of these two values jeopardizes the applicability of these papers since the decisions cannot rely on the "unknown" underlying true value. In fact, the evolution of human perception of reserves influences decisions on field development. 3) These papers mainly address real options "on" projects (valuation of managerial flexibility, such as start/defer/stop options), although some interesting results were shown on drilling, and platform capacity expansion flexibility. Real options "on" projects do not provide much information on how to design flexible systems, and where to embed flexibility. 4) Several papers apply optimization-based approaches (i.e., stochastic programming, GA) to search for optimal designs under uncertainty, but optimization-based approaches are generally computationally expensive if a more realistic systems model and uncertainty models have been used. Furthermore, point-optimal solutions will become sub-optimal if the assumptions that were used for optimization change.

In summary, several research gaps have been identified in the literature. To address these gaps, this thesis contributes to academic research and practice in the following aspects:

- This thesis proposes and demonstrates a framework for exploring flexible strategies under uncertainty using an integrated screening model. The contribution is not on developing the screening model for petroleum projects itself, but the framework and simulation strategy for exploring flexible strategies using a screening model. This framework captures the interactions among multiple domains and takes into account a system's exogenous and endogenous uncertainty, and simulates how decision makers should modify the systems as uncertainties unfold. Overall, the framework provides a computational laboratory to experiment with different development strategies efficiently.
- With respect to the real options literature, this thesis extends the previous work on real options "in" projects and develops a framework to explore flexible strategies in petroleum projects. In particular, this thesis develops a stochastic reservoir uncertainty model to mimic the evolution of human perception of reserves.
- With the engineering systems design literature, this thesis promotes and demonstrates a holistic view of uncertainty and flexibility. Both system endogenous and exogenous uncertainties have been taken into account, and three levels of flexibility (strategic level, tactical level, and operational level) have been identified and modeled.
- To the oil and gas industry, this thesis yields relevant applications of offshore project planning, particularly during project appraisal, conceptual design, and development stages. The integrated modeling and simulation framework provides decision makers a computational laboratory to experiment with different flexible strategies before locking-in a rigid development plan. This approach and tools can be applied during the appraisal and select stages of a petroleum project.

# Chapter 3: Screening Flexible Strategies in Engineering Systems

## 3.1 Introduction

An Engineering System is complex due to the complexity within each domain (or discipline) and interactions among these domains. Furthermore, an engineering system is not an isolated entity, and it continuously interacts with the external environment over its lifecycle. Effective conceptual designs and development plans underpin the success of all engineering systems. Development strategies need to be flexible enough to adapt to endogenous or exogenous uncertainty. It is not a trivial task to identify promising flexible strategies given the complex interactions among multi-domains and their uncertainties. Traditional engineering practice focuses on searching for "the optimal" design given deterministic conditions or assumptions. Recognizing and taking into account multi-domain uncertainties in systems' designs and development requires a completely different mindset. It is a conceptual leap for decision makers and system architects to shift their focus from the optimal designs to flexible designs. In the early phases of a project, decision makers and system architects can easily be overwhelmed by many design alternatives and vast amounts of uncertainty. Traditional point-optimal design methodology cannot effectively explore flexible designs under uncertainty because the optimal solution under deterministic conditions will not remain optimal as uncertainties evolve over time or assumptions become invalid. It is usually not effective in terms of time and resources required to re-design and modify existing development plans if such modifications are not anticipated ahead of time. Re-design of original prototypes may be the only alternatives if the customer or contract requirements are unknowable (such as for aircraft engines). However, for capital-intensive systems with multi-domain uncertainty (such as petroleum systems), it is imperative to have a screening phase, which explores the design space quickly and screens for promising flexible strategies during the conceptual study and development planning stages. The screening phase is then followed by detailed engineering designs and economic evaluations, where management of "no change" is paramount to project success.

This chapter further explains the generic simulation framework for screening flexible strategies under multi-domain uncertainty as shown in Figure 7 . There are five key elements in this framework:

1) An architecture alternative generator: is a front-end tool to generate a large number of technically feasible architectures, that can then be evaluated using the screening models under multi-domain uncertainties. This architecture alternative generator (e.g., OPN based architecture tools) is part of ongoing research and is not included in this thesis. This thesis assumes that initial architectures are given, and Design of Experiments (DOE) is applied to setup a set of candidate strategies to be evaluated by the screening models.
2) Uncertainty modeling and simulation: is one of the key elements of this framework. It is very important to identify uncertainty in multiple domains and develop appropriate models to simulate them. With simulation models that capture uncertainty, decision makers and system architects can simulate how strategies perform under a variety of circumstances. To identify and model the entire uncertainty space for generic engineering systems may be a very challenging task. This chapter therefore focuses on petroleum systems, and shows how to develop stochastic models for reservoir uncertainty, facility uncertainty, and market uncertainty in petroleum projects.
3) An integrated screening model: is a simplified representation of technical systems and economical value. The screening model is the instrument for simulating and exploring strategies. Chapter 4 is devoted to this topic. In chapter 4, we first argue why mid-fidelity screening models are needed and how they are different from traditional high-fidelity models and low-fidelity optimization models, and we then propose a generic screening model with resource systems, production systems, and output systems. Finally we demonstrate this approach by developing a screening model for petroleum projects.
4) Multi-level flexibility over the lifecycle of a project: Generally, there are different levels of flexibility for decision makers, such as strategic flexibility, tactical flexibility, and operational flexibility. But it is not a straightforward process to identify, model, and evaluate these flexibilities due to the complexity of the systems and the surrounding multi-domain uncertainty. Flexibility enables systems to respond to uncertainty in pro-active

ways. Chapter 5 focuses on this topic, and three levels of flexibility for petroleum projects are identified and illustrated.

5) Decision rules: encode how to exercise built-in flexibilities (e.g., modifying system architectures or operations) as uncertainties unfold. Intelligent decision rules capture the human learning behavior and provide an automatic mechanism to simulate flexible strategies under uncertainty. This chapter gives a generic description for decision rules, and proposes an approach to experiment and fine tune decision rules. Examples of decision rules will be provided for the case studies in Chapters 6 and 7.

In summary, this chapter focuses on 2) uncertainty modeling and simulation and 5) decision rules, Chapter 4 focuses on 3) the integrated screening model, and Chapter 5 focuses on 4) multi-level flexibility. This thesis demonstrates this framework by applying it to two case studies in the petroleum domain (i.e., flexible staged development for a hypothetical large oilfield, tieback flexibility for small oilfields) in Chapters 6 and 7, respectively.

## 3.2 Recognizing and Modeling Multi-domain Uncertainties

Engineering systems are planned, designed, developed and operated in an uncertain environment. Uncertainties come from many domains, such as the technical, economic, political, and social domains. A successful engineering system should be able to react to these uncertainties in favorable ways. Some uncertainties, such as technical uncertainty, can be directly managed and reduced by investments in systems. However, other uncertainties, such as market uncertainty and socio-political uncertainty cannot be directly managed or influenced by decision makers or system architects. In between, there are some uncertainties, such as development cost and schedule uncertainties, over which decision makers and system architects have only partial control and influence. Various uncertainty classification frameworks have been proposed in the literature. For example, de Weck *et al.* (2007) identify the sources of uncertainty (i.e., endogenous, exogenous) and their contexts (i.e., product, corporate, user, market, political and culture contexts) for early product and system design as shown in Figure 15 in Chapter 2. Built on the current literature, this section further develops a generic uncertainty classification framework for engineering systems, and applies this framework to petroleum projects.

Depending on the sources of uncertainty and the levels of influence that decision makers can have, we classify uncertainty into the following three categories:

- Endogenous uncertainty: Endogenous uncertainty is embedded in systems, such as technical uncertainty. Decision makers and system architects can actively direct and manage the evolution of endogenous uncertainty by investment in the projects (i.e., investment in appraisal well drilling to reduce reservoir uncertainty or technology development to ensure success). Therefore, the evolution of endogenous uncertainty depends on the system designs and development plans. Moreover, the evolution of this type of uncertainty is attached to the time frame of system designs and development plans. Without any investment in the systems, endogenous uncertainty may not resolve by itself. Since understanding of endogenous uncertainty requires domain knowledge of the systems, scientists and engineers are responsible to provide information on endogenous uncertainty. In general, this type of uncertainty is expressed as probability distributions of technical parameters. Further, the evolution of these probability distributions depends on the projects' investments, system designs, development plans, and operations.
- Exogenous uncertainty: Compared to endogenous uncertainty, exogenous uncertainty is independent of technical systems. Examples of such uncertainty include market uncertainty (i.e., commodity prices, market demand). Decision makers and system architects generally do not have direct influence on the evolution of exogenous uncertainty. Furthermore, the evolution of exogenous uncertainty does not depend on the choice of designs and development plans. Exogenous uncertainty evolves according to its own dynamics. Most of the real options literature deals with design under exogenous uncertainty. Several stochastic models, such as Geometric Brownian Motion (GBM), and the lattice model, have been developed to simulate the evolution of exogenous uncertainty.
- Hybrid uncertainty: This type of uncertainty falls in between the previous two categories. The evolution of hybrid uncertainty can only be partially influenced by decision makers and system architects. Development uncertainty is an example of hybrid uncertainty. In general, development uncertainty, such as development cost, schedule, and contract uncertainty, depends on not only system designs and development plans but also market

conditions. So decision makers or system architects only have partial influence on this type of uncertainty. Modeling and simulating hybrid uncertainty would require knowledge of technical systems and market conditions. In the project risk management literature, researchers address the cost, schedule, and performance uncertainty for complex product development. For example, Browning (1998) applies the Design Structure Matrix (DSM) method, causal loop analysis, and stochastic simulation approaches to model and analyze the impact of project cost, schedule and performance uncertainty / risk on complex system product development.

Table 8 compares these three types of uncertainties and illustrates them in petroleum projects. Under this classification framework, one important distinction can be made whether the uncertainty originates from human perception (or limited knowledge of the system) of a static value or the uncertainty variables are stochastic by themselves. For petroleum projects, reserve estimate uncertainty is due to human's limited knowledge of reservoirs but the characteristics of the reservoirs themselves (such as Original Oil In Place (OOIP)) have evolved to a (quasi) steady state over millions of years. In contrast, market uncertainty (such as crude oil and gas prices) is characterized by dynamic and non-stationary processes as crude oil or gas prices evolve into the future. Compared to the standard stochastic models (e.g., Geometric Brownian Motion, binomial tree) for market uncertainty, the evolution of reserve estimates requires different stochastic models, which need to capture the human learning processes of the underlying static values.

**Table 8:** Three types of Uncertainty

| Types of uncertainty | From decision makers or system architects' perspective | From system designs and development plans' perspective | Example: petroleum project | Uncertainty modeling and simulation approaches |
|---|---|---|---|---|
| **Endogenous uncertainty** | Evolution of the uncertainty can be actively controlled or managed | Evolution of the uncertainty depends on system designs and development plans. | Subsurface uncertainty (geological, reservoir),surface (facility) uncertainty | Probability modeling of parameters for technical systems, Bayesian learning model |
| **Exogenous uncertainty** | Evolution of the uncertainty is independent of any decisions by decision makers or system architects | Evolution of the uncertainty is independent of system designs and development plans. | Market uncertainty: i.e., market prices for hydrocarbon products | Geometric Brownian Motion (GBM), Lattice model, Monte Carlo simulation |
| **Hybrid uncertainty** | Evolution of the uncertainty can be partially influenced by design choice | Evolution of the uncertainty is partially dependent on system designs and development plans. | Development uncertainty: i.e., cost, schedule, contract (jointly influenced by technical and market uncertainties) | Monte Carlo simulation, discrete event modeling, signal flow graph method, System Dynamics, Design Structure Matrix |

### 3.2.1 Endogenous Uncertainty for Petroleum Projects

For a petroleum project, endogenous uncertainty mainly refers to technical uncertainty such as subsurface (i.e., geology structures, reservoirs) and surface (i.e., the performance of production facilities) uncertainty. The evolution of these uncertainties can be influenced by decision makers or system architects by making investments in the project, such as drilling more appraisal wells to reduce subsurface uncertainty, adding redundant equipment to increase process reliability and reduce downtime uncertainty. A detailed discussion of endogenous uncertainty for petroleum projects is illustrated as follows:

**Subsurface uncertainty**

Subsurface uncertainty represents all "underground" uncertainties, such as geological structures for hydrocarbon reservoirs, fluid compositions and properties, quantity and quality of initial hydrocarbons in place (i.e., Stock tank Original Oil In Place (STOOIP)), drive mechanisms (i.e., primary, secondary, enhanced recovery) for production, and the recovery factor. Among these uncertainties, uncertainties in volume of initial hydrocarbons (e.g., STOOIP) and recoverable hydrocarbons (e.g., reserve) are the most critical for decision makers and system architects in the development planning stage of a hydrocarbon basin.

The quantity of hydrocarbons determines the development scale for a hydrocarbon basin (i.e., number of platforms, number of wells, facility capacities, connections among fields and facilities). However, the quantity of hydrocarbons is highly uncertain especially in the early stages of a field development. Even in the operations stage, the estimates of recoverable hydrocarbons can change significantly if new geological structures (i.e., fault, sealing) and reservoir conditions (i.e., aquifer support) are discovered. STOOIP is the term to describe the amount of oil in standard surface conditions. In practice, STOOIP is estimated by the volumetric estimation method. The formula (Jahn, Cook, and Graham, 1998) to calculate the initial volume of oil is as follows:

$$STOOIP = GRV \cdot \frac{N}{G} \cdot \phi \cdot S_o \cdot \frac{1}{B_o} \qquad \text{[Eq. 3 - 1]}$$

$$Ultimate\ Recovery = STOOIP \cdot Recovery\ Factor \qquad \text{[Eq. 3 - 2]}$$

$$Reserve = Ultimate\ Recovery - Cumulative\ Production \qquad \text{[Eq. 3 - 3]}$$

Where

*STOOIP:* stands for stock tank original oil in place. It normalizes volume of oil present in subsurface conditions (high pressure and temperature) to the standard surface conditions (i.e., 1 bar, 15 $^{o}$C).

*GRV*: is Gross Rock Volume of the hydrocarbon-bearing interval. It can be estimated based on the area containing hydrocarbons and the interval thickness.

*N/G:* is Net to Gross Ratio (N/G). It is the ratio between the thicknesses of productive reservoir rock within the total (gross) reservoir thickness.

$\phi$: is porosity for productive reservoir rock. It is the percentage of volume for bearing fluids within reservoir rock. $GRV \cdot \frac{N}{G} \cdot \phi$ gives the total pore space for bearing fluids (oil and water) and gas.

$S_o$: is oil saturation. It is the percentage of pore space which contains oil.

$B_o$: is the oil formation volume factor, which transforms volume at reservoir conditions to standard surface conditions. $1/B_o$ transforms a reservoir barrel (rb) to standard surface barrel (stb). $B_o \sim$ [rb/stb].

*Ultimate Recovery (UR)* and *reserve* are linked to volumes initially in place by the recovery factor, which is a fraction of the initial volume.

*Reserve:* is equal to ultimate recovery before production occurs. *Reserve* represents the amount of hydrocarbons (and value) that can be extracted from an oilfield. Reserves decrease over time as a fraction of ultimate recovery.

*Recovery Factor (RF):* depends on reservoir drive mechanisms and production schemes.

All the parameters for calculating *STOOIP* are uncertain. They are estimated using various techniques. For example, seismic surveys and exploration well drilling can be used to estimate reservoir location and area, and core samples can be used to estimate the net gross ratio, volume formation factor, and porosity. Given the heterogeneous nature of an oilfield, the values for these parameters may vary across fields. For offshore petroleum fields, it is very expensive (\$10~\$100 million per well) to get log samples by drilling wells. Thus, the estimates of these parameters are generally uncertain given limited samples. Therefore, the estimates of *STOOIP* and *reserve* are uncertain. Quantifying the uncertainty of *STOOIP* and *reserve* is one of the major tasks for subsurface teams in the early stages of field development. In practice, these uncertainties are expressed in terms of probability distributions or cumulative probability distributions (called expectation curves in petroleum engineering). In petroleum engineering, there are two general ways to estimate the distributions of *STOOIP* (and *reserve*):

1) Monte Carlo simulation: Input parameters are sampled from their assumed distributions. Each sample combines these uncertain inputs and obtains one instance of *STOOIP*. After obtaining a large number of samples, a frequency histogram can be obtained to approximate the probability distributions of *STOOIP*.
2) Parametric method: This is an established statistical technique used for combining variables containing uncertainties. This method is based on basic statistical rules to add or multiply multiple uncertain variables if each variable can be characterized by a distribution with its own mean and standard deviation.

In the following section, an example is provided to illustrate how to use Monte Carlo sampling and parametric methods to estimate *STOOIP* and *reserve*.

Table 9 shows the assumed distributions for input parameters. In this example, all distributions are assumed normal. The Monte Carlo sampling results are based on 5000 samples. Figure 20 and Figure 21 show histograms and expectation curves respectively. The estimated distributions for STOOIP and reserve appear to be lognormal. This is not a surprise since probability theory (as an extension of the central limit theorem, Rice, 1995) says that the product of multiple independent normal (or any) distribution variables is a lognormal distribution. The expectation curve shown in Figure 21 is essentially a cumulative distribution function (CDF). For example, a point (200, 0.2) on the curve means that there is a 20% chance that the reserve is greater than 200 mmbbls. For a prospect field, there is a finite probability to have zero recoverable hydrocarbons. Therefore, the expectation curve will not reach one.

**Table 9:** Input parameters for STOOIP and reserve estimates

| Input parameters | Assumed distribution | Definition of distribution |
|---|---|---|
| $GRV$ | Normal distribution | Mean = $10^{10}$ barrels, std = 3 *$10^9$ |
| $N/G$ | Normal distribution | mean =0.4, std = 0.1 |
| $\phi$ | Normal distribution | mean = 0.5, std = 0.1 |
| $S_o$ | Normal distribution | Mean = 0.2, std= 0.03 |
| $B_o$ | Normal distribution | Mean = 1.2, std = 0.1 |
| $RF$ | Normal distribution | Mean = 0.4, std = 0.1 |

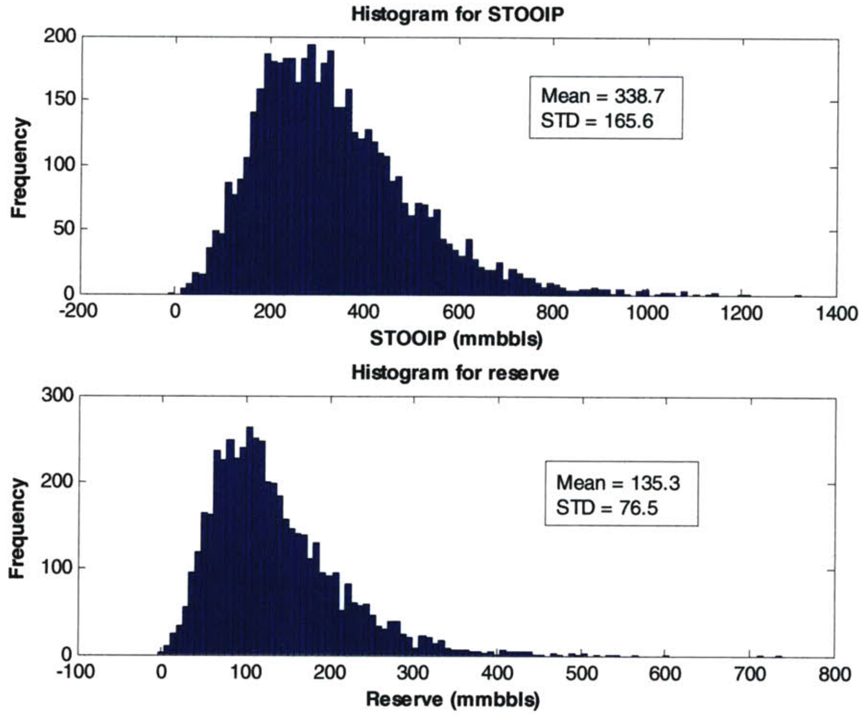


**Figure 20:** Histograms for STOOIP and Reserve[3]

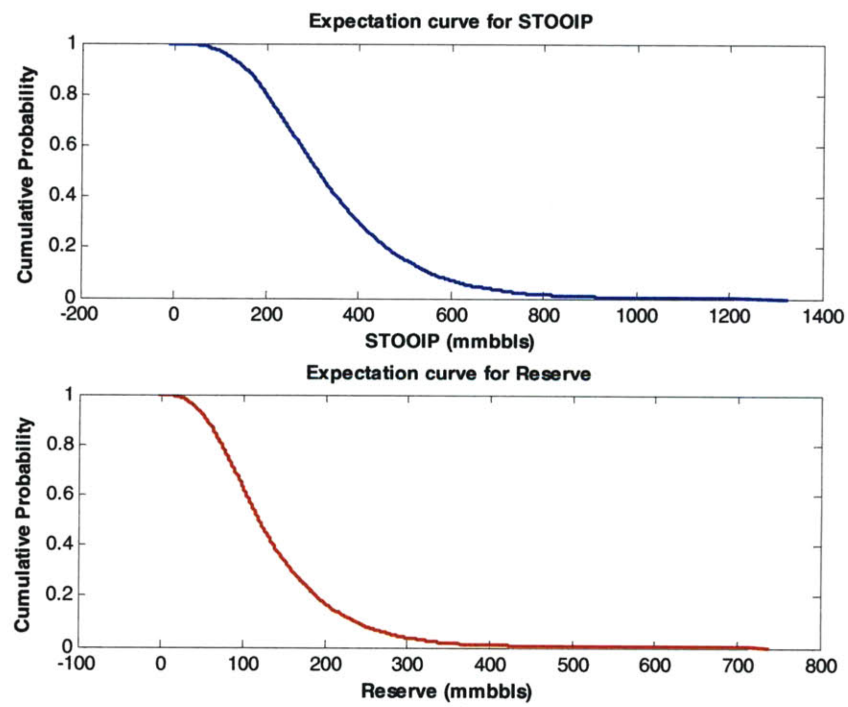


**Figure 21:** Expectation curves for STOOIP and Reserve

[3] mmbbls: million barrels (for crude oil in standard surface condition)

Monte Carlo sampling is very easy to implement with current computing resources and easily available software (i.e., Crystal Ball, @risk, Matlab, Excel), but it does not reveal how much the uncertainty of each input parameter contributes to the overall uncertainty. The parametric method provides a convenient way to estimate the relative contribution of each input parameter's uncertainty. If we assume the inputs are independent of each other, the relative contribution of each input parameter to the overall uncertainty is $(1+K_i^2)$, where $K_i = \sigma_i / \mu_i$ for each input parameter (Jahn, Cook, and Graham, 1998). Applying this formula to the previous example, Figure 22 shows the relative impact of input parameters on uncertainty of STOOIP and reserves.

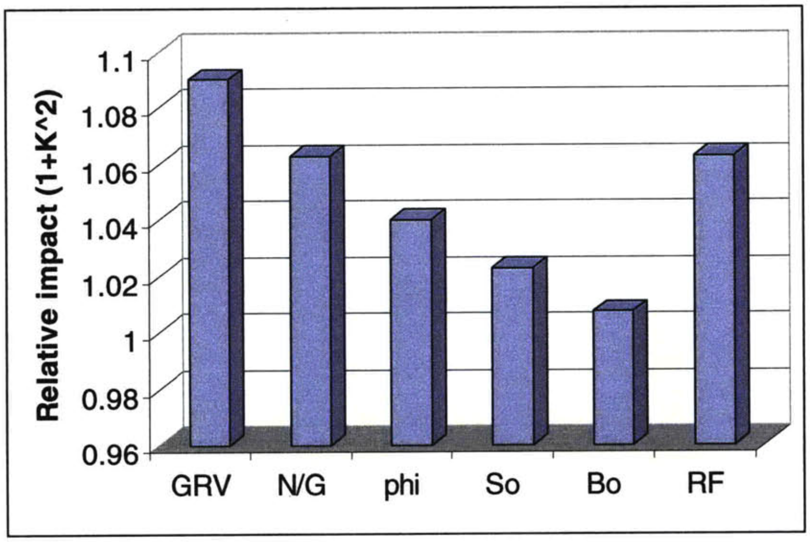


**Figure 22:** Relative impact of input parameters on uncertainties in STOOIP and Reserve

Both Monte Carlo sampling and the parametric method for subsurface uncertainty assessment have been widely applied in practice. However, the uncertainty approach is still static in the sense that it only provides a snapshot of uncertainty at a given point in time. In practice, new information becomes available from field studies, and reservoir engineers need to constantly update the uncertain inputs for reservoir simulation models. Quite often, updating of the uncertainty inputs for reservoir simulation models cannot keep up with the arrival of new information, because significant amount of time[4] and effort would be required to transfer data between different discipline-based tools, and to perform model setup and updates with new information. Thus, information to make decisions is sometimes outdated and does not reflect

[4] An informal survey suggests that 2/3 of engineers' time is spent on data transfer and model setup, and only 1/3 is spent on actual computation in the oil and gas industry.

current best knowledge of reality. Therefore, it is imperative to have ways 1) to simulate the possible evolution trajectories of subsurface uncertainties; 2) to develop flexible strategies that are capable to adapt to future uncertainty. To address these two needs, this thesis develops an evolution model for subsurface uncertainty and an integrated modeling and simulation framework to screen flexible field strategies under multi-domain uncertainties. This section focuses on the evolution model for subsurface uncertainty.

**Evolution of subsurface uncertainty**

Subsurface uncertainty refers to reservoir uncertainty in petroleum E&P projects, such as uncertainty in the volume of recoverable hydrocarbons underground. It is an important source of uncertainty that influences the strategic planning of field exploration and development. To some extent, the unfolding of subsurface uncertainty drives the direction and progression of projects. For major oil companies, a significant amount of resources have been spent on quantifying and managing subsurface uncertainty. A reservoir is a complex geological system and many factors (e.g., geology structures, rock properties, and fluid characteristics) contribute to the recoverable hydrocarbon volume, which is one of the most important inputs to determine the economic value of a project.

However, there is an important distinction between unknown "true" conditions of reservoirs and human perception (i.e., estimates of these parameters). A reservoir's geological structures, fluid properties, and quantity and quality of hydrocarbons are in fact "deterministic" as they are physical entities and they have evolved over millions of years to a quasi steady-state before any external interference, such as exploration, appraisal, and production well drilling occurs. However, the human perception (or estimation) of reservoir physical conditions is evolving over time as new information is acquired through exploration and production. The decisions on field development are made based on human perception of reservoir conditions instead of the underlying "true" values, which are unknown.

The true quantity of hydrocarbons is a deterministic number. It is unlikely to change in a short period of time. However, the estimates of hydrocarbons (both quantity and quality) are uncertain.

Through investment in the project, such as seismic surveys, appraisal well drilling, and production testing, more information is gathered which hopefully reduces the uncertainty of reserve estimates over time. Figure 23 illustrates the concepts of evolution of subsurface uncertainty. It assumes that at any given point of time, the estimate of an uncertain variable (i.e., STOOIP, reserve) follows a distribution characterized by a mean and standard deviation. The green line represents one possible trajectory for the estimated mean. It is assumed that the estimated mean progressively approaches the "true" underlying value. This trajectory may not be monotonic. But there is some possibility that the estimate initially approaches a "false" underlying value, and then suddenly the estimate changes significantly as new information is discovered about the reservoir. For example, as shown in Figure 23, the estimate of reserve decreases significantly at $t_2$ which may be due to discovery of a new fault structure in a reservoir, which reduces flow connectivity among different compartments of the reservoir. In theory as well as in practice, it is also possible that the true underlying value is greater than the initial estimate. For example, the actual hydrocarbon-bearing area or porosity turns out to be much higher than the initial estimates. In Figure 23, $\Delta\mu$ represents the initial estimation error for mean, which determines "the level of sub-optimality" for a design based on the initial estimate. The green line represents one trajectory for the mean estimate among many possibilities for a new project. However, for any past project, there is only one "realized" estimation trajectory. Therefore, one of the interesting research questions to ask is:

***How to simulate evolution trajectories for an epistemic uncertain variable (on which decisions are based)?***

In this chapter, we propose a stochastic model to simulate the evolutionary trajectories for reserve estimates. This stochastic uncertainty model includes discrete jumps in the estimate trajectory. Chapter 5 of this thesis argues that recognizing possible future jumps in reserve estimates is critical for decision makers. Flexibilities in design enable projects to better adapt to such jumps. The purpose of the evolution model is not to predict jumps (e.g., exact timing and magnitude), but to simulate potential jumps and evaluate how well that flexible strategies (and their decision rules) can help systems adapt to such disruptive changes in the future by exercising built-in flexibility. Although the precise timing and magnitude of the jumps are unknowable in the beginning, a good flexible strategy should be able to mitigate negative jumps (e.g., not exercising capacity expansion flexibility, designing smaller initial stages) and take advantage of positive jumps (e.g., exercising capacity expansion flexibility).

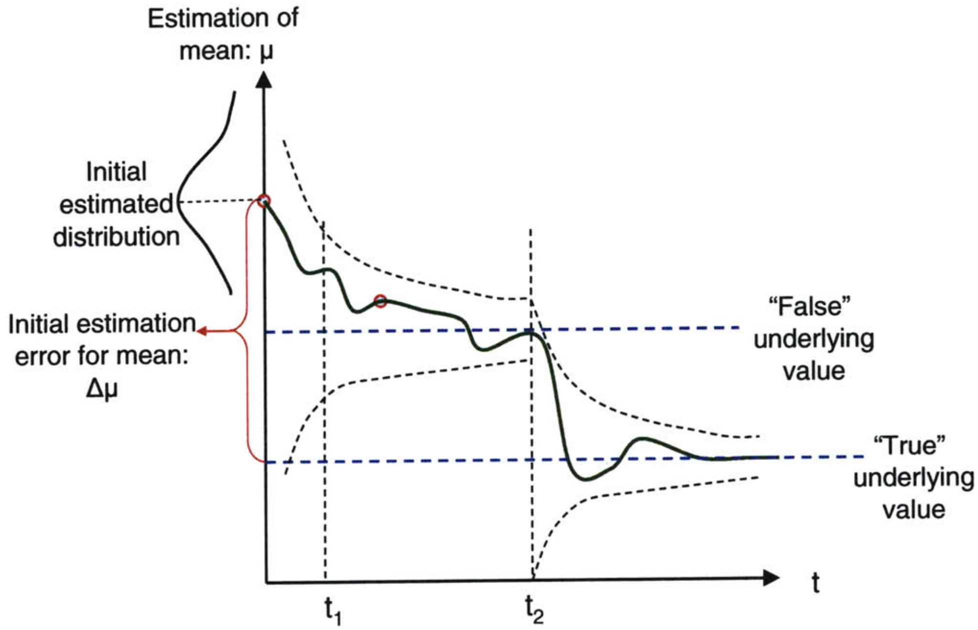


**Figure 23:** Evolution of subsurface uncertainty

Uncertainty evolution concepts are motivated by real world examples. Figure 24 shows the distribution of two projects' reserve estimates from exploration discovery to the end of appraisal. There are several observations from these two examples: First of all, there is a general trend of uncertainty reduction over time. In the first example in Figure 24, the range between P10 and P90 narrows from exploration discovery to end of appraisal, although it is not a monotonic reduction. Secondly, there are some discontinuous "jumps" in median (P50) estimates. When these jumps occur, the range of uncertainty increases simultaneously. Thirdly, it is possible for the range of uncertainty to increase without a jump as shown in the second graph.

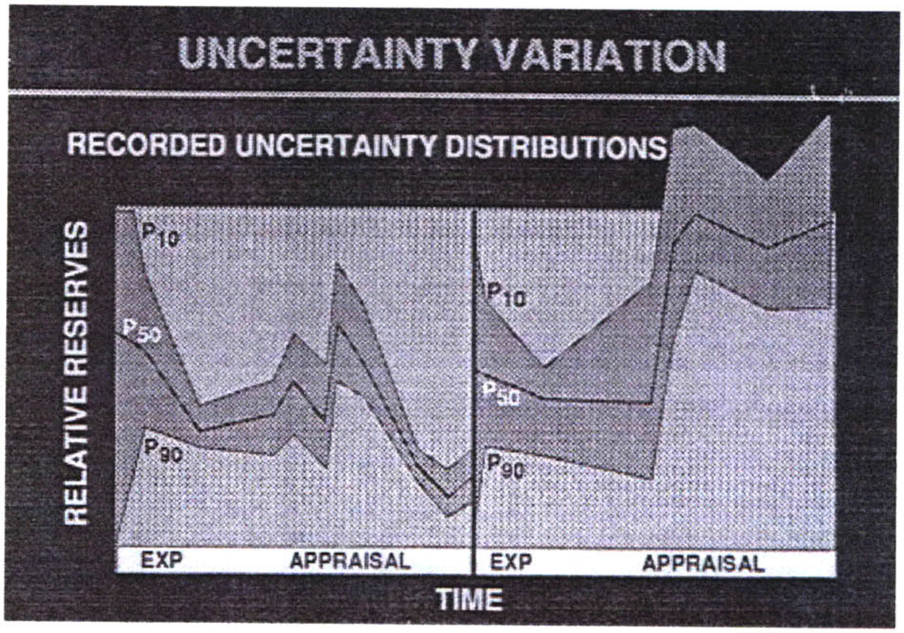


**Figure 24:** Two projects' reserve estimates from exploration discovery to end of appraisal (Source: BP)

They are many reasons that can drive the evolution of reserve estimates. First, as projects progress from exploration to production, knowledge of reservoirs accumulates over time through seismic surveys and analysis, exploration and appraisal well drilling, and production. Ideally, the range of uncertainty in reserve estimates reduces progressively and eventually approaches the unknown true values. In many cases, not until oil production starts to decline (see typical production profile as shown in Figure 18), can true reservoir dynamics be fully observed and understood (see production profile curve). Therefore, uncertainty reduction in reserve estimates results from learning processes through active scientific and engineering activities, which cannot be obtained without capital investment (usually millions or billions of dollars) and time (tens of years from exploration to production). Secondly, there is some possibility that the estimates of reserve have "disruptive jumps." These discontinuous changes may be due to the discovery of static reservoir structures (e.g., faults) and dynamic behaviors (e.g., aquifer support). These new discoveries will potentially cause a reversion of previous reserve estimates and they can happen at different stages of the field lifecycle. In general, the probability of having such discrete jumps is higher in the early stages as there is limited knowledge about reservoirs.

Because the decisions on field development, such as sizing a facility, are largely driven by human perception of the unknown "true" value, it is necessary to be able to simulate the possible evolution trajectories of reserve estimates over time, on which development decisions are based. In petroleum engineering, extensive research focuses on quantifying and modeling subsurface (i.e., reservoir) uncertainty, however, to the author's knowledge, little research is found on modeling and simulating the evolution processes of reserve estimates by capturing human learning (both progressive learning and "surprise" change) processes. Given the nature of this problem, there are two types of modeling approaches:

1) <u>Data-driven approach for reservoir uncertainty modeling</u>: This approach requires samples of previous projects with historical data on reserve estimates, and applies statistical techniques (i.e., regression, response surface method) to fit empirical models (with fitted parameters) to the distribution of reserve estimates and their evolutionary behavior.

2) <u>Analytical approach for reservoir uncertainty modeling</u>: This approach assumes an initial distribution for uncertain reservoir variables and uses several parameters to describe the distribution (i.e., mean, variance) and the evolutionary behavior (i.e., speed of convergence, probability of disruptive jumps) of reserve estimates over time. Once an analytical model is in place, it can be calibrated based on available data. As the project progresses, new data (i.e. new reserve estimates) can be utilized to update the parameters of the analytical model on the fly using a Bayesian approach (Delft-Stanford workshop on closed-loop reservoir management, 2004)

There are several limitations for the first approach: First, it requires a large number of samples in order to estimate model parameters with statistically significant tests. In practice, it is very challenging to get access to a reasonable number of samples for reservoirs' historical data, particularly over the past 15~30 years given the trend in corporate acquisition and mergers in the late 1990s. Secondly, since each reservoir (or project) is unique, the estimated parameters tend to mix reservoirs with distinct geological characteristics. As a result, the model with "averaged" parameters is not very relevant to any particular reservoir. Furthermore, the historical data on reserve estimates tends to be used to interpret how significantly the initial development decisions were off. Therefore, in general, managers are reluctant to release this kind of information to third parties to avoid mis-use or mis-interpretation.

Given the challenges of the first approach, this thesis develops a stochastic reservoir uncertainty model based on an analytical approach. By making some initial assumptions on reserve estimates (i.e., type of distribution, speed of convergence), this approach avoids requiring large samples of historical data. But it allows updating the model parameters on the fly by using the Bayesian learning approach. Therefore, the model can be tuned to a specific reservoir by acquiring more information from the reservoir or benchmarking to other similar reservoirs. The rest of this section presents a stochastic reservoir uncertainty model. This model is setup by several parameters and an analytical procedure for implementing changes to the distribution of estimates over time. Then, this method can generate an ensemble of possible evolutionary trajectories of reserve estimates. As time progresses, actual reserve estimate data can be used to update the model parameters. The overall reservoir uncertainty modeling framework is illustrated in Figure 25.

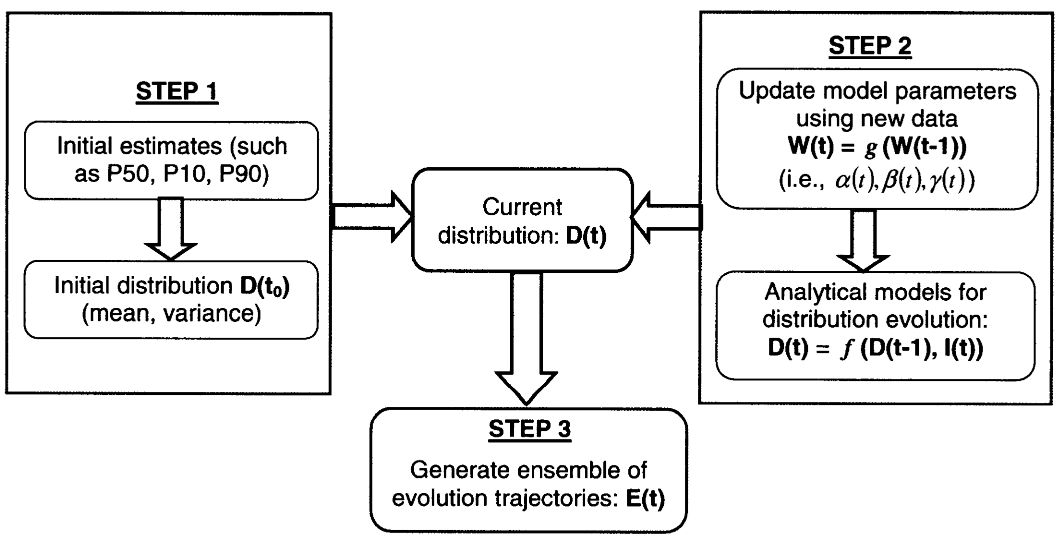


**Figure 25:** Modeling framework for reservoir uncertainty

The first step is to transform an initial reserve estimate into a probability distribution, such as lognormal distribution characterized by vector $\boldsymbol{D}(t_0)$ containing the moments of the distribution (mean and standard deviation). The second step is to update the distribution vector $\boldsymbol{D}(t)$ from the previous time step $\boldsymbol{D}(t-1)$. In this process, the model parameters vector, $\boldsymbol{W}(t)$, needs to be updated if an actual reserve estimate becomes available. If the information is not available, $\boldsymbol{W}(t)$ remains the same as $\boldsymbol{W}(t-1)$. The third step is to generate an ensemble of reserve estimate trajectories $\boldsymbol{E}(t)$ given the model. In this model, there are two functions, the first one is the update function[5] $\boldsymbol{W}(t) = \boldsymbol{g}(\boldsymbol{W}(t-1))$, which updates model parameters using available data, such as historical data of reserve estimates. The other one is the distribution evolution function $\boldsymbol{D}(t) = \boldsymbol{f}(\boldsymbol{D}(t-1), \boldsymbol{W}(t))$, which updates the mean and variance of reserve estimates.

The rest of this section will demonstrate how to operationalize this generic modeling framework. The modeling process can be summarized in the following three steps:

***STEP 1: Generate An Initial Distribution Vector $\boldsymbol{D}(t_0)$***

The initial inputs and assumptions on reserve estimates include the following:

- Inputs for the first step include the initial reserve estimate, such as P0 ~ P100 on reserve estimates, which are generally available for prospect, discovery and appraisal fields. Table 10 gives the initial reserve estimates for a hypothetical prospect.
- At any given point in time, we assume that reserve estimates follow a lognormal distribution, which is characterized by its mean[6] ($\mu$) and standard deviation ($\sigma$). These two parameters are estimated using the least square method – search for mean and standard deviation to minimize the sum of residuals' square $\sum_{i=1}^{k} r_i^2$, where r are the residuals between input data and estimations of the fitted model for P10 ~ P90. Because the theoretical P100 for a lognormal distribution is infinity, we ignore the P100 data point for the least square curve fitting.
- For a prospect[7] field, there is a finite probability of having zero recoverable hydrocarbons. The probability distribution of *reserve* can be approximated by a delta function (finite probability with zero reserve) plus a "scaled" lognormal distribution..

[5] One type of update function is based on Bayesian theory, however, if new information (such as simulating future events) is not available, we assumes that *W(t) = W(t-1)* in this thesis.
[6] Mean and sigma here are defined for the random variable *log(x)*, where *x* follows a lognormal distribution.
[7] For a prospect field, there is a finite probability of having zero recoverable reserve underground; for a discovery field, it is certain that the recoverable reserve is positive.

For example, Figure 26 shows the cumulative distribution curve by least square fitting based on the data in Table 10. The fitted initial distribution is a scaled lognormal distribution plus a delta function. Figure 27 shows the simulated initial probability distribution for *reserve* estimated based on the fitted model. In this example, three parameters are used to define the initial distribution at time $t_0$, and the estimated values by the least square curve fitting are shown as follows:

$$\boldsymbol{D}(t_0) = \begin{bmatrix} \mu(t_0) \\ \sigma(t_0) \\ \lambda(t_0) \end{bmatrix} = \begin{bmatrix} 3.36 \\ 0.44 \\ 0.2 \end{bmatrix}$$

The initial distribution includes two parts:

- Scaled lognormal distribution for cumulative probability from 0 to (1-$\lambda(t_0)$). Given the initial inputs in Table 10, the estimated mean and standard deviation for the scaled lognormal distribution are: $\mu(t_0) = 3.36$, $\sigma(t_0) = 0.44$.
- Delta function for cumulative probability from (1-$\lambda(t_0)$) to 1. There is a finite probability -- $\lambda(t_0)$ -- to have zero recoverable hydrocarbons. For the initial inputs shown in Table 10, $\lambda(t_0)$ is equal to 0.2.

**Table 10:** An example of initial reserve estimates
(Resources are normalized based on the initial P50 estimate)

| | P100 | P90 | P80 | P70 | P60 | P50 | P40 | P30 | P20 | P10 | P0 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Initial inputs | 0 | 0 | 0 | 0.57 | 0.82 | **1.00** | 1.18 | 1.36 | 1.57 | 1.89 | 3.82 |
| Predictions | 0 | 0 | 0 | 0.71 | 0.88 | 1.02 | 1.18 | 1.36 | 1.59 | 1.96 | |

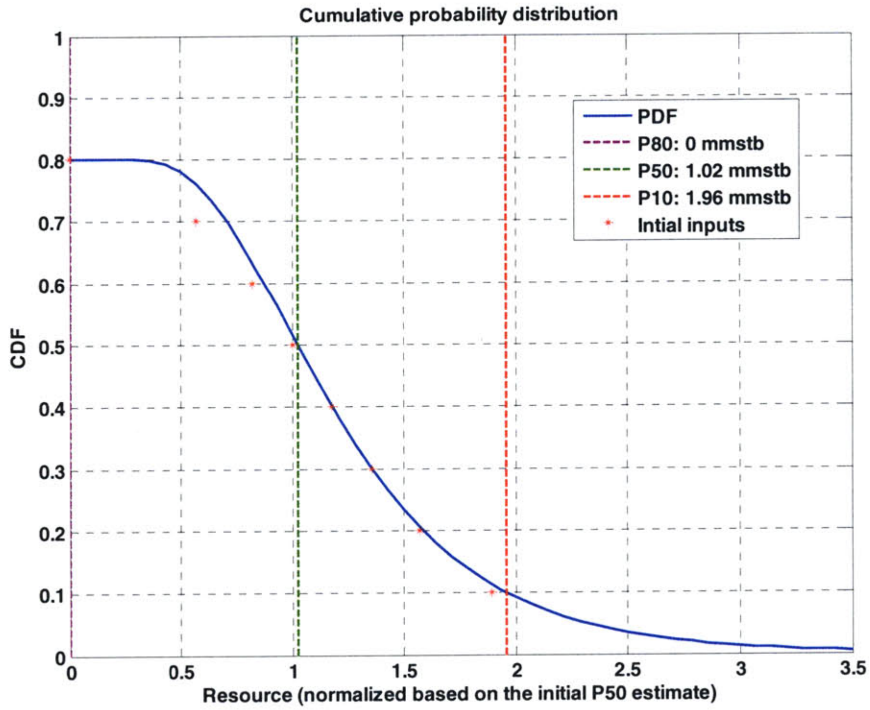


**Figure 26:** A fitted cumulative probability distribution

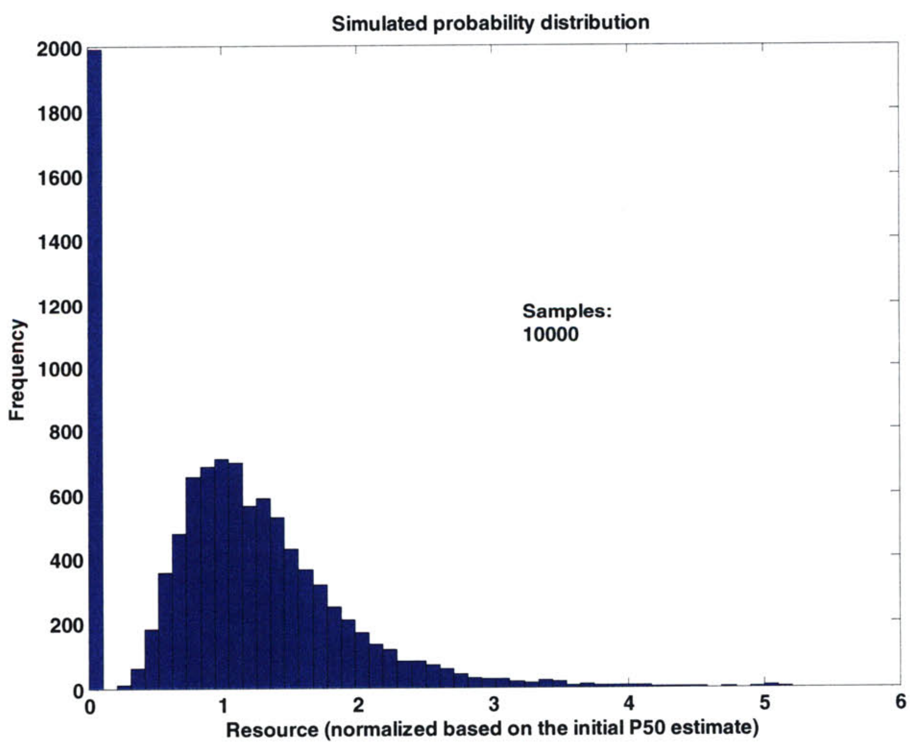


**Figure 27:** Simulated probability distribution at $t_0$

***STEP 2: Update the Distribution Vectors D*(t) *at Time t***

The second step is to update the distribution vector $\boldsymbol{D}$ from time t-1 to t. A set of parameters and functions will define how each element of $\boldsymbol{D}$(t) evolves over time.

- $\mu(t)$: There are two assumptions that define the evolution of $\mu(t)$ in the following equation: First, it assumes that the mean of $log(reserve)$ starts from the initial estimate and follows a random walk at each time step. Secondly, the variation of random walk is assumed to decrease exponentially over time. Ideally, this decrease rate should be estimated from historical data (if available) in a similar geographical region. It also assumes that the probability for a discrete jump decreases exponentially. Hence, the following equations can be used to define the evolution of $\mu(t)$:

$$\mu(t) = \mu(t-1) + \Delta_t \qquad \text{[Eq. 3 - 4]}$$

$$\begin{cases} \Delta_t = b\Sigma_0 e^{-\beta_r} & if \quad a \geq p_r(t) \\ \Delta_t = c\Sigma_0 & if \quad a < p_r(t) \end{cases} \qquad \text{[Eq. 3 - 5]}$$

$$p_r(t) = p_r(t_0)e^{-\gamma(t-t_0)} \qquad \text{[Eq. 3 - 6]}$$

Where

$p_r(t)$: the probability for discrete change at time t

$\beta_r$: exponential decline rate for the variation of random walk

$\gamma$: exponential decline rate for the probability of disruptive change

$a$: a random number drawn from uniform distribution between 0 ~ 1

$b$: a random number drawn from standard normal distribution

$c$: a random number drawn from uniform distribution between 0.5 ~ 1.5.

$\Sigma_0$: the initial standard variability for random walk of log(P50) , default [0.2].

- $\sigma(t)$: It assumes that the standard deviation of $log(reserve)$ starts from an initial value and decreases exponentially. Whenever the mean has a disruptive change, the variance increases simultaneously.

$$\begin{cases} \sigma(t) = \sigma(t-1)e^{-\alpha} & if \quad a \geq p_r(t) \\ \sigma(t) = \max\left(\sigma(t-1)e^{-\alpha} \quad d\sigma_0\right) & if \quad a < p_r(t) \end{cases} \qquad \text{[Eq. 3 - 7]}$$

Where

$\alpha$ : exponential decline rate for the standard deviation of $log(reserve)$

$d$ : a random number drawn from a uniform distribution between 0.5 ~ 1

- $\lambda(t)$: this parameter is non zero for a prospect field, which has a finite probability of having a zero reserve. For discovered fields, $\lambda(t) = 0$. If no future information is available, the model assumes this parameter remains at the initial estimate. If future information is available, it is possible to estimate the evolutionary trend for $\lambda(t)$. For simplicity, the model shown in this thesis assumes:

$$\lambda(t) = \lambda(t_0) \qquad \text{[Eq. 3 - 8]}$$

Equations 3-4 through 3-7 define the function ***g*** for each element of ***D***(t), where function ***g*** updates ***D***(t) from time step t-1 to t. (***D***(t)=***g***(***D***(t-1),***W***(t))). The model parameters ***W***(t) can also be a function of time. ***W***(t) includes parameters, such as $\alpha(t)$, $\beta_r(t)$, and $\gamma(t)$, to define the various exponential decline rates. If new reserve estimates become available over time, the parameters vector should be updated according to the Bayesian approach. If only a snap shot of reserve estimates is available, we assume that model parameter vector ***W***(t) is a constant vector. The concept for updating model parameter vectors is illustrated as follows:

$$\begin{cases} W(t) = W(t-1) & \text{if} \quad I(t) \in \phi \\ W(t) = f(W(t-1), \quad I(t)) & \text{if} \quad I(t) \notin \phi \end{cases} \qquad \text{[Eq. 3 - 9]}$$

where *I*(t) represents new information at time t, such as actual estimate (instead of projection of estimate) of reserve at time t. The Bayesian approach can be applied to define the parameter update function ***f***. However, this thesis does not define this function based on the Bayesian framework. Developing Bayesian learning models would need actual data (not generally available in practice) and require different mathematical procedures. This thesis develops a stochastic model to mimic possible learning processes.

Equation 3-9 shows that ***W***(t) = ***W***(t-1) if the new information *w*(t) is not available (as an empty set $\phi$), otherwise, the update function ***f*** has to be defined in order to take into account new information $I$(t) in the process of updating the model parameter factor $\boldsymbol{W}$(t). The model parameter vector is defined as follows:

$$W(t) = \begin{bmatrix} \alpha(t) \\ \beta_r(t) \\ \gamma(t) \end{bmatrix}$$

An extended version of the $\boldsymbol{W}$(t) vector would also need to include the parameters $a$, $b$, $c$, and $d$. to completely define the model, we have to define the initial conditions of the model: $\sigma(t_0)$, $\Sigma_0$, and $p_r(t_0)$.

With this model, we can generate an ensemble of possible evolutionary trajectories for reserve estimates given the best knowledge of reservoirs today. However, the actual evolution history for reserve estimates is only one instance. This is the main difference between human perception of reserve evolution (many possible evolutionary trajectories) and the actual evolution history for the reserve estimate (only one evolutionary trajectory). The ensemble of future scenarios can be used as inputs to simulate strategic decision making of field development in the early planning stages. The ensemble of reserve evolution trajectories allows decision makers to experiment with various field development strategies in view of possible reserve evolutions. In this type of application, since the future has not yet unfolded, there is no need to update the model parameter vector $\boldsymbol{W}$(t), which can be assumed as a constant vector $\boldsymbol{W}$($t_0$). The next step describes how to generate an ensemble of future scenarios using Monte Carlo simulations.

***STEP 3: Generate an Ensemble of Future Scenarios: E*(t)**

An ensemble of future scenarios $\boldsymbol{E}$(t) is generated using Monte Carlo simulations. In Matlab, there are built-in functions for sampling from a given distribution (such as uniform, normal, lognormal distribution). The simulation is discretized in a small time step (such as 3 ~ 12 months over a 25 year lifecycle). Within each simulation time step, samples are drawn from given distributions, and the evolution of reserve estimates is simulated according the formula from steps 1 and 2. Figure 28 shows two evolution trajectories for reserve estimates. These two trajectories start from the same initial estimate and diverge in different directions. In year 11, one of the trajectories has a disruptive jump for reserve estimates. As a result, the range of uncertainty increases simultaneously. But in this model, the estimate of the *reserve* has a high probability to converge monotonically over time to the true unknown value.

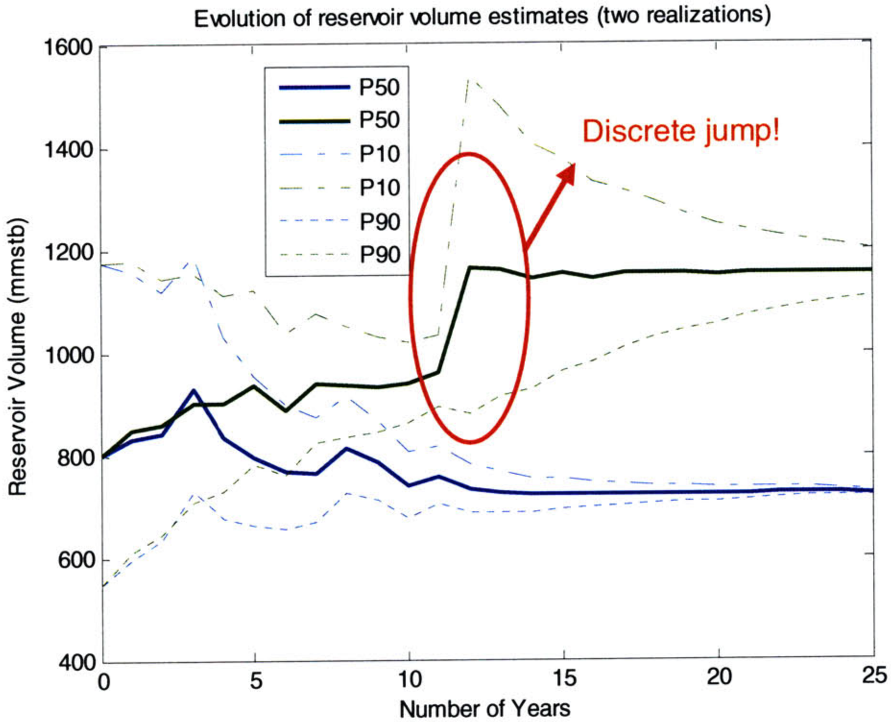


**Figure 28:** Two evolution trajectories of reserve estimates
(Assumed model parameters: $\alpha = 0.15$, $\beta_r = 0.2$, $\gamma = 0.15$, $\sigma_0 = 0.3$, $\Sigma_0 = 0.2$, $p_{r0} = 0.05$)

### Surface uncertainty

Surface uncertainty in petroleum projects includes any technical uncertainties above the ground on sea level, from wellheads, to topside production facilities, to export pipelines performance. While subsurface uncertainty comes from a lack of knowledge of natural systems, surface uncertainty is the uncertainty that originates from within engineered systems. Subsurface and surface uncertainties are not independent, and sometimes subsurface uncertainty will propagate to surface uncertainty. For example, the uncertainty of reservoir drive mechanism (e.g., existence of aquifer support) induces uncertainty in the installation of water injection pumps.

Surface uncertainty has been recognized and studied in the academic literature and in industry practice. Major surface uncertainty includes:

- Facility uptime and availability: Topside facilities include many subsystems, such as separators and compressors, and export systems. Overall system uptime and availability depend on each subsystem's reliability and their interactions. Generally, a probabilistic simulation approach is used to evaluate systems' reliability and availability. In the oil and gas industry, specialized software, such as P-choke, has been developed and widely applied. More sophisticated facility reliability models have also been developed in other domains (e.g., aerospace, nuclear industry). For example, Wertz (2006) developed the Expected Productivity Risk Analysis (EPRA) approach to model and simulate the systems' expected productivity. The proposed approach is applied to the terrestrial planet finder interferometer mission. In general, the changing state of facilities (e.g., uptime, downtime) can be modeled as Markov Chain processes.
- Injection streams: This includes the uncertainty in timing of injections, the quantity and quality of injection streams (water and/or gas). The injection uncertainty is primarily driven by subsurface uncertainty, such as whether or not there is aquifer support, or gas cap support in a given reservoir.
- Well performance: This includes many parameters, such as productivity, availability, pressure, which can all be uncertain during production stages.
- Facilities' spare capacity: the amount of spare capacity for facilities can be uncertain as the incoming fluids' quantity, quality, and properties are uncertain (such as produced water handling as water break through occurs into well bores).

In order to demonstrate the impact of surface uncertainty on petroleum projects as shown in Chapters 6 and 7, this section develops a model to simulate facility availability uncertainty. Facility availability is defined as the percentage (range from 0 to 100%) of the actual availability of capacity relative to the designed capacity. Facility availability is the result of wells, subsea equipment, and platform availability. And it is subject to well drilling ramp-up, the facility commissioning schedule, operating conditions, and environmental conditions (such as hurricanes). Therefore, facility availability is uncertain. We propose a model to simulate facility availability starting from project ramp-up to decommissioning. This facility availability model includes three key components:

*1) Expected facility availability*

Figure 29 illustrates the Expected Facility Availability (EFA) curve, which includes a ramp-up period and a steady state period. The EFA is defined as follows:

$$EFA(t) = \begin{cases} 1 - e^{\beta_f t} & if \quad t \le t_{ramp\_up} \\ b & if \quad t > t_{ramp\_up} \end{cases} \qquad \text{[Eq. 3 - 10]}$$

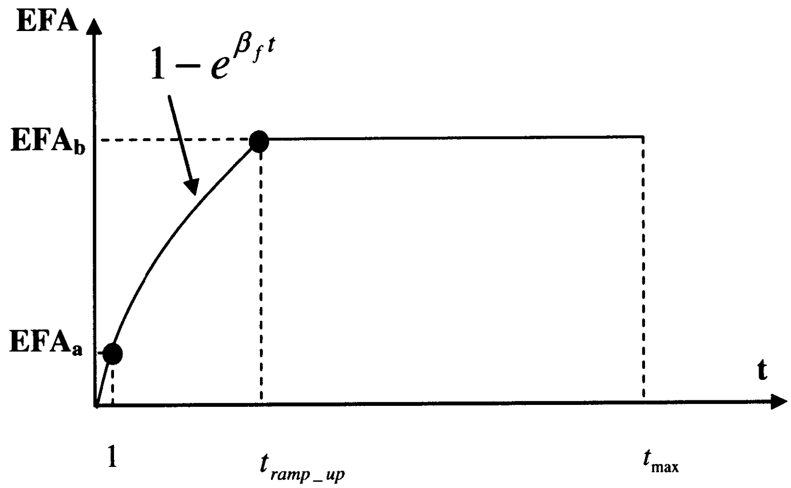


**Figure 29:** Expected Facility Availability

Where $t$ is months of production starting from "first oil", $t_{ramp\_up}$ is the production ramp-up time and it is assumed to be equal to well drilling ramp-up time. However, in reality $t_{ramp\_up}$ can be a random variable as well due to the uncertainty in the schedule of production ramp-up. If we assume the expected facility availability at first oil is $EFA_a$ and the expected facility availability at the steady state is $EFA_b$, the parameter $\beta_f$ can be estimated by curve fitting as shown in following:

$$\begin{cases} 1 - e^{\beta_f} = EFA_a \\ 1 - e^{\beta_f t_{ramp\_up}} = EFA_b \end{cases}$$

Solving this equation, we get $\beta_f$:

$$\beta_f = \frac{1}{t_{ramp\_up} - 1} \log\left(\frac{1 - EFA_a}{1 - EFA_b}\right) \qquad \text{[Eq. 3 - 11]}$$

2) *A "Random walk" component for Facility Availability (FA).* This model assumes that at any given point in time the FA is sampled from a normal distribution which is centered at $EFA_b$.

$$FA(t) \sim N(EFA(t), \quad \sigma)$$

where $\sigma$ is the standard deviation for the normal distribution. When a sample $FA(t)$ is greater than 1, its value is set to 1 since $FA(t)$ falls within the range from 0 to 1. Similarly, if a sample $FA(t)$ is less than 0, its value is set to 0.

3) *"Significant events" for the FA, such as facility shutdown due to hurricanes.* This simulation model also takes into account with a certain probability, $p_f$, that facilities are shut down entirely due to "significant events", such as hurricanes or for safety consideration (such as preventative maintenance). $p_f$ is set a 0.05 (as default), which mean there is a 5% chance in any given time period that the facility will be shut down, and that as a result, $FA(t)$ is equal to zero. Figure 30 shows an instance of the $FA(t)$.

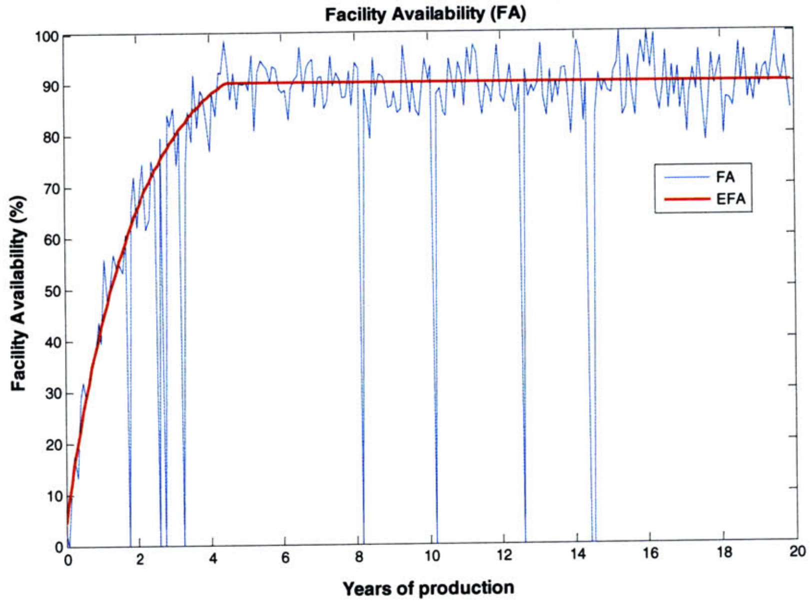


**Figure 30:** Simulation of facility availability
(Assumed parameters: $EFA_a = 0.05$, $EFA_b = 0.9$, $\beta_f = 0.043$, $p_f = 0.05$, $t_{ramp\_up} = 4.5$ years, $\Delta t_f = 3$ months, $t_{\max} = 20$ years)

Understanding and managing surface uncertainty would require an integrated team with facility, process, and subsurface engineers. However, modeling surface uncertainty is not the primary focus of this thesis. Chapter 5 will propose flexibility in design as a way to manage both subsurface and surface uncertainties.

### 3.2.2 Exogenous Uncertainty for Petroleum Projects

There are many uncertainties, which are beyond the direct control and influence of oil companies. These can be grouped into exogenous uncertainty, such as uncertainties of the market prices for hydrocarbon products, business environment, and macroeconomic environment. They are all very critical for the success of a petroleum project. For exogenous uncertainty, this thesis particularly focuses on market uncertainty, such as oil and gas spot prices.

Continuous stochastic processes such as Geometric Brownian Motion (GBM) and Wiener processes, and discrete models such as the lattice model, have been developed and widely applied to model the evolution of market uncertainty. This section will briefly review the GBM and lattice models, and then develop a binomial tree model to simulate the uncertainty of crude prices using historical data.

Geometric Brownian Motion (GBM) and Wiener Processes

Brownian motion originally refers to the observed random motion of a pollen when immersed in water under a microscope. The notion of Brownian motion was then developed by physicists (i.e., Einstein, Markov, and Wiener) as a stochastic process. It was not until the 1960s that the theory of Brownian motion was applied to model stock prices.

GBM is a continuous stochastic process in which the logarithm of a random variable, such as stock price, follows a Brownian motion, or a Wiener process. Let's apply GBM to model the evolution of oil/gas market prices. Let $P$ be the spot price of crude oil and assume it follows a Geometric Brownian Motion. Within a time interval $\Delta t$, the change of $P$ is $\Delta P$. The following equation describes the rate of change for oil price ($\Delta P / P$) in a discrete time version:

$$\frac{\Delta P}{P} = \mu \Delta t + \sigma \varepsilon \sqrt{\Delta t} \qquad \text{[Eq. 3 - 12]}$$

where $\varepsilon$ is a random number drawing from a standard distribution, $\mu$ is the expected mean drift rate during the time interval, and $\sigma$ is the standard deviation for $\Delta P / P$ if $\Delta t = 1$. Thus, $\Delta P / P$ has a normal distribution with mean and variance as follows:

$$E\left[\frac{\Delta P}{P}\right] = \mu \Delta t, \qquad \text{[Eq. 3 - 13]}$$

$$\text{var}\left[\frac{\Delta P}{P}\right] = \sigma^2 \Delta t \qquad \text{[Eq. 3 - 14]}$$

The expected value and volatility of $\Delta P / P$ increase linearly with respect to the duration of the discrete time step. The mean and volatility can be estimated from historical data, such as past oil/gas prices[8]. Figure 31 shows the historical crude oil price from 1946 up to May 2008. Literature in Econometrics and Finance mathematics proposes various more theoretical approaches to estimate parameters for stochastic processes (i.e., GBM, two-factor model, stochastic processes with jumps) to model the evolution of stock prices or commodity prices. Since market uncertainty modeling techniques have been developed and widely applied in the real options literature (de Weck *et al.*, 2004; Wang, 2005), this section provides a practical approach to estimate model parameters for GBM.

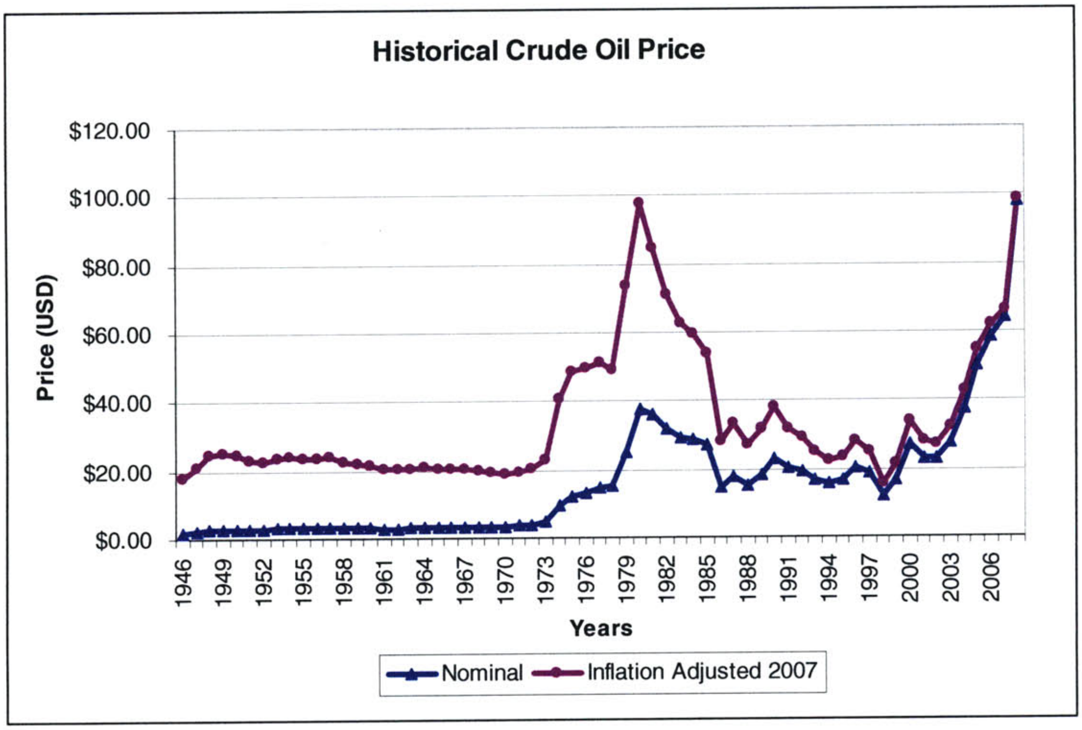


**Figure 31:** Annual averaged crude oil price (1946 ~ May, 2008)
(Note that crude oil prices peaked at $150 in July 2008 and back in the $50 range in November, 2008)

To estimate the annual expected drift rate $\mu_m$ for crude oil price, we assume an exponential growth model for the mean as follows:

$$P(t) = P(0) \cdot (1 + \mu_m)^t \qquad \text{[Eq. 3 - 15]}$$

[8] Historical crude price (1948~2008) is available from:
http://www.inflationdata.com/inflation/Inflation_Rate/Historical_Oil_Prices_Table.asp (up to May, 2008)

where $P(0)$ is the initial crude oil price, t is the year and ranges from 0 to 62 (corresponding to 1946~2008). Equation 3-12 assumes a discrete time interval $\Delta t = 1$ year. By taking a natural logarithm on both sides of the equation, we obtain the following equation:

$$\ln(P(t)) = \ln(P(0)) + (1 + \mu_m) \cdot t$$

Applying the linear regression model on the natural logarithm scale of historical data, the parameters can be estimated as:

$$\begin{cases} \ln(P(0)) = 3.04 \\ 1 + \mu_m = 1.012 \end{cases}$$

Therefore, the estimated initial crude oil price (in 1946) $P(0) = \$20.94$ per standard barrel and the expected mean drift rate is 1.2% per annum. Figure 32 shows the regression model and historical data in natural log-scale.

The remaining parameter is the volatility $\sigma$ of crude oil prices. Since the underlying crude oil is assumed as a lognormal distribution (like stock prices) by the definition of GBM, the volatility can be estimated based on the standard deviation of the natural logarithm of the crude oil price. However, the variation due to mean drift needs to be subtracted from the data[9]. Therefore, the volatility is estimated as standard deviation based on the following data set:

$$\left(\ln(P(t)) - \ln(P(t)^{estimated})\right) - \left(\ln(P(t-1)) - \ln(P(t-1)^{estimated})\right)$$

Where t = 1~n. $\left(\ln(P(t)) - \ln(P(t)^{estimated})\right)$ is the mean drift adjusted data set. Since ln(P(t)) accumulates a random term $\sigma_m \varepsilon$ at each time interval, subtracting ln(P(t)) from its previous time step will give a sample of $\sigma_m \varepsilon$ within the time interval. Because $\varepsilon$ is a random number drawn

[9] There is another approach: if the standard deviation of the natural logarithm of oil price is taken as volatility, then the mean drift rate needs to be adjusted, by Ito's lemma: $d\ln(P) = (\mu - \frac{\sigma^2}{2})dt + \sigma dz$

from standard normal distribution, the standard deviation of $\sigma_m \varepsilon$ is $\sigma_m$. Based on the mean drift adjusted data set, the estimated volatility is $\sigma_m$ = 19.5% per annum. Given the estimated parameters, Figure 32 simulates the simulated crude price over 30 years based on the GBM model.

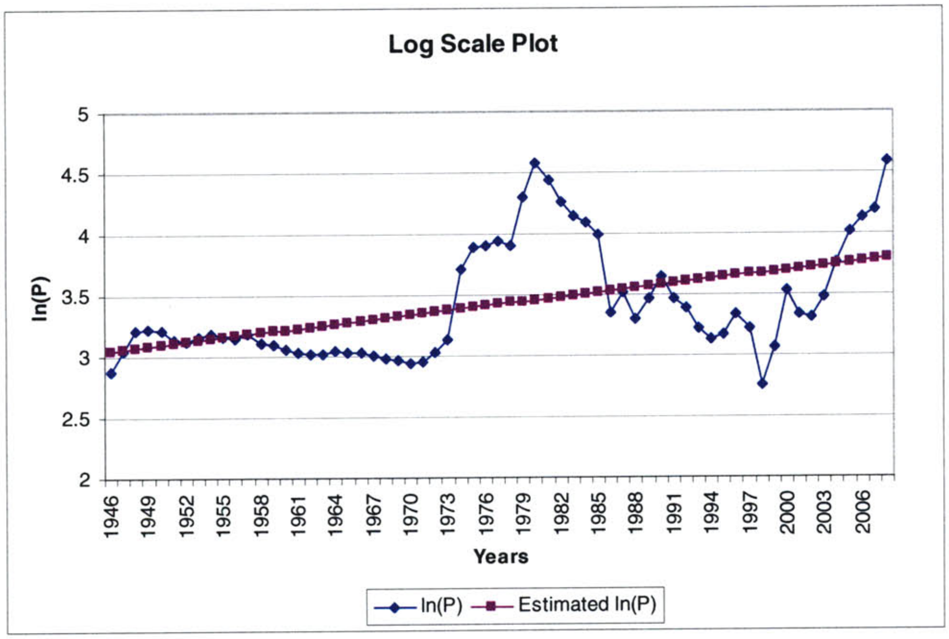


**Figure 32:** A least square curve fit in natural logarithm scale (estimated ln(P) drift only)

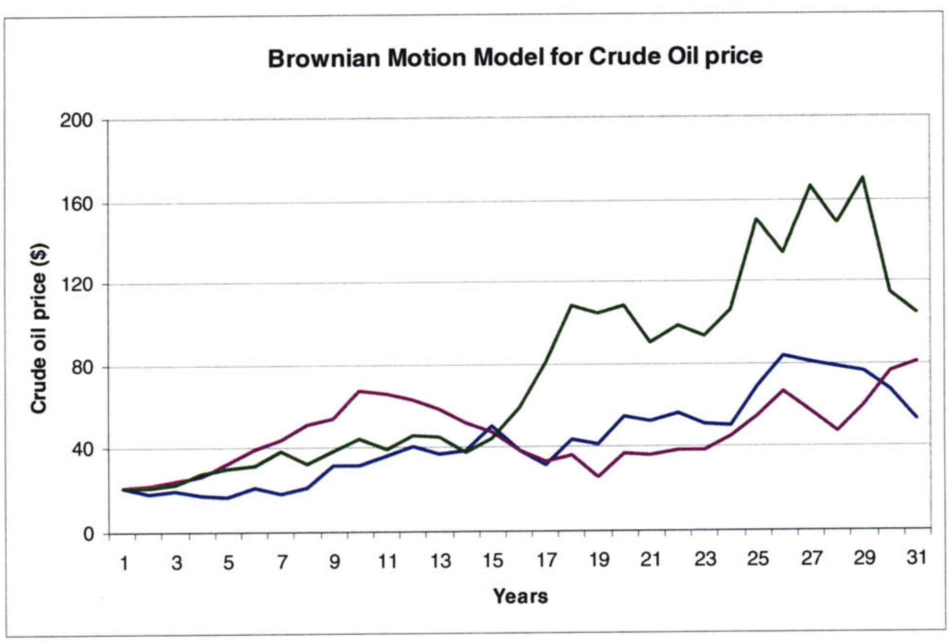


**Figure 33:** Three evolution trajectories for crude oil price based on the GMB model (Assumed parameters: $P_0 = \$20.94$, $\mu_m = 1.2\%$ p.a., $\sigma_m = 19.5\%$ p.a.)

## Lattice Model

Brownian motion has an infinite number of future scenarios. In general, the Monte Carlo simulation technique is applied to obtain a sample of future scenarios. The lattice model is an alternative approach to model market uncertainty. It assumes at each discrete time step that a stochastic variable (i.e., stock price, demand, and crude oil price) can only make a finite numbers of moves ("up" or "down" for binomial lattice model). The lattice model enables the recombination of stochastic values, thus the total numbers of values at each time step only grows linearly with the number of time steps. For a binomial lattice model, we assume that the stochastic variable may move up (*u*) or down (*d*) with a probability *p* and *1-p*, respectively. Equation 3-7 must hold in order to maintain statistical equivalence between GBM and the binomial lattice model. The volatility and length of the discrete time step determines the magnitude of up or down move.

$$\begin{cases} u = e^{\sigma_m \sqrt{\Delta t}} \\ d = \dfrac{1}{u} \\ p = \dfrac{e^{u\Delta t} - d}{u - d} \end{cases} \qquad \text{[Eq. 3 - 16]}$$

Figure 34 shows the binomial lattice model for crude oil prices, where the annual drift rate and volatility are assumed as 2% and 10% respectively. This model simulates the evolution of crude oil price over 30 years with a discrete time step of 3 years. There are in total 10 discrete time steps. The bold red line represents one trajectory out of 1024 ($2^{10}$) scenarios. The probability for a particular scenario can be computed as:

$$p(i) = p^k (1-p)^{n-k} \qquad \text{[Eq. 3 - 17]}$$

Where $n$ is the number of time steps and $k$ is the number of time steps when the price moves up, $i$ represents an instance of the project evolution trajectories, $i$ ranges from 1 to 1024 in this particular example. It is important to note that not all trajectories are equally likely to occur.

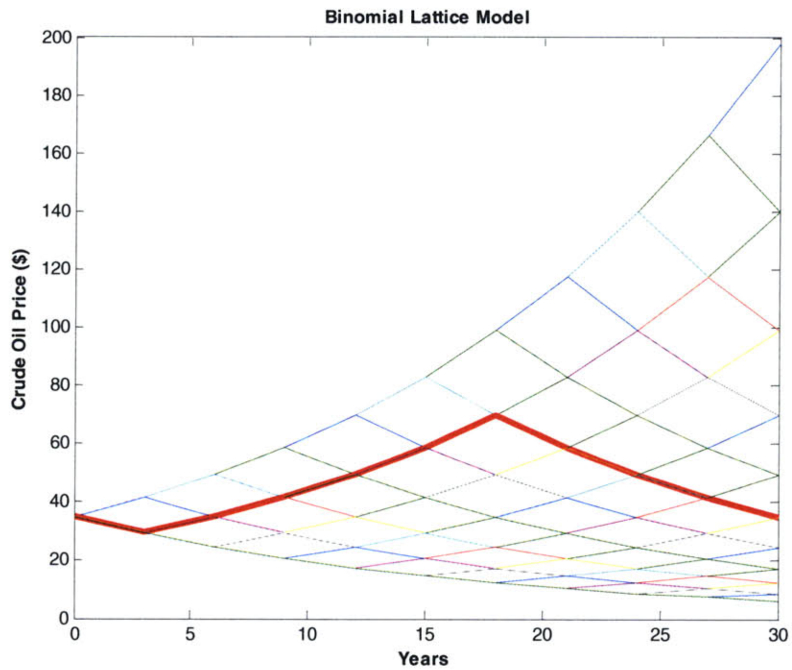


**Figure 34:** A Binomial Lattice Model for Crude Oil Price
(Assumed parameters: $P_0 = \$35$, $\mu_m = 2\%$ p.a., $\sigma_m = 10\%$ p.a., $\Delta t_m = 3$ year)

### 3.2.3 Hybrid Uncertainty for Petroleum Projects

Hybrid uncertainty falls in between projects' endogenous and exogenous uncertainties. The evolution of hybrid uncertainty is determined jointly by choice in systems' design and project external forces, such as market conditions and the political environment. For petroleum projects, hybrid uncertainty includes development cost, schedule, contract uncertainty, etc.

- Development cost and schedule: From a technical perspective, development cost largely depends on geographical locations (onshore vs. offshore, water depth), geological characteristics (reservoir structure, fault, sealing,), the sizes of reservoirs (the amount of hydrocarbons), technology (well types, drilling technology, subsea architecture, concepts for topside platforms, production equipment), etc. From a market perspective, the development cost is also influenced by the supply and demand relationship for the entire supply chain, from raw materials, drilling equipment and services, construction, transportation, to commissioning. For example, in recent years, the increase in crude oil price has attracted a lot of investment in offshore projects. As a result, the demand for drilling rigs and services has skyrocketed. Many oil companies are experiencing, significant cost inflation due to the imbalance of supply and demand for raw materials, drilling services, and construction. The same reasoning applies to project uncertainty. Therefore, the development cost and schedule are uncertain due to both embedded technical uncertainty in projects as well as market uncertainty. Traditionally, this is the area of research on risk management in projects (Browning, 1998). Given the scope defined in Chapter 1, this thesis does not intend to address development cost and schedule uncertainty, which is an area worthy of future research in Engineering Systems. However, a facility availability model has been developed in the previous section, which takes into account the schedule (i.e., production ramp-up) uncertainty during a project's ramp-up stages.

- Contract Uncertainty: there are different types of contracts for petroleum projects. At the program level (includes multiple projects in a hydrocarbon basin), a Production Sharing Agreement (PSA) is the contract signed by the host government and contractor group (a joint-venture by several oil companies). A PSA defines the terms of how to recover investment costs and how to split production revenues between the host government and the contractor group. A PSA sometimes is subject to changes given the political, and economic uncertainties in the host country. At a project level, there are service, operations, and construction contractors. All these contracts have a certain degree of uncertainty given the technical complexity and market uncertainty for petroleum projects. Contractual uncertainty for petroleum projects by itself is a worthy different research topic. This thesis does not intend to address contractual uncertainty.

## 3.3 Decision Rules for Exploring Different Strategies

Complex engineering systems are being planned, designed, developed and operated in the presence of multi-domain uncertainty. Decision makers or system architects need to make important system level decisions while these uncertainties are still evolving. In a good development strategy, these decisions about system design and development are flexible enough to accommodate future changes. Flexible strategies retain degrees of freedom for system architects to change the configuration of the systems, or for system operators to modify the mode of operations of the systems. However, it is very difficult to identify a good strategy among many possibilities given the complexity and uncertainty of many engineering systems. This thesis proposes a simulation-based approach to explore different strategies under uncertainty. One of the core ingredients for this approach is to use decision rules to mimic human decision under different circumstances.

A decision rule is a prescription for conditional actions. It states what actions are to be taken as certain conditions are satisfied. These conditions can be based on uncertain variables. Some actions need to be taken while uncertainty is not completely resolved. It may either be too costly to acquire information to reduce the uncertainty or the uncertainty cannot be resolved (aleatoric uncertainty). There are many different ways to represent decision rules, such as decision trees (Wang, 2005), decision networks (Silver and de Weck, 2007), and logical (Boolean) statements.

**1) <u>Decision Trees</u>**

Decision trees have long been used to represent contingency plan of actions. Decision Tree Analysis (DTA) is a standard system analysis and scenario planning tool under uncertainty. In general, uncertain variables are discretized at several intervals and several contingency actions can be chosen as the uncertainty unfolds over time. Figure 35 shows an example of a decision tree for the development planning of satellite systems. Deployment decisions are based on the demand evolution over time. For technical systems, the decision tree is path dependent, which means that the different paths in the decision tree have different evolution trajectories for architectures even when the uncertain variables reach the same final state. Decision tree analysis is one of the techniques used in real option analysis.

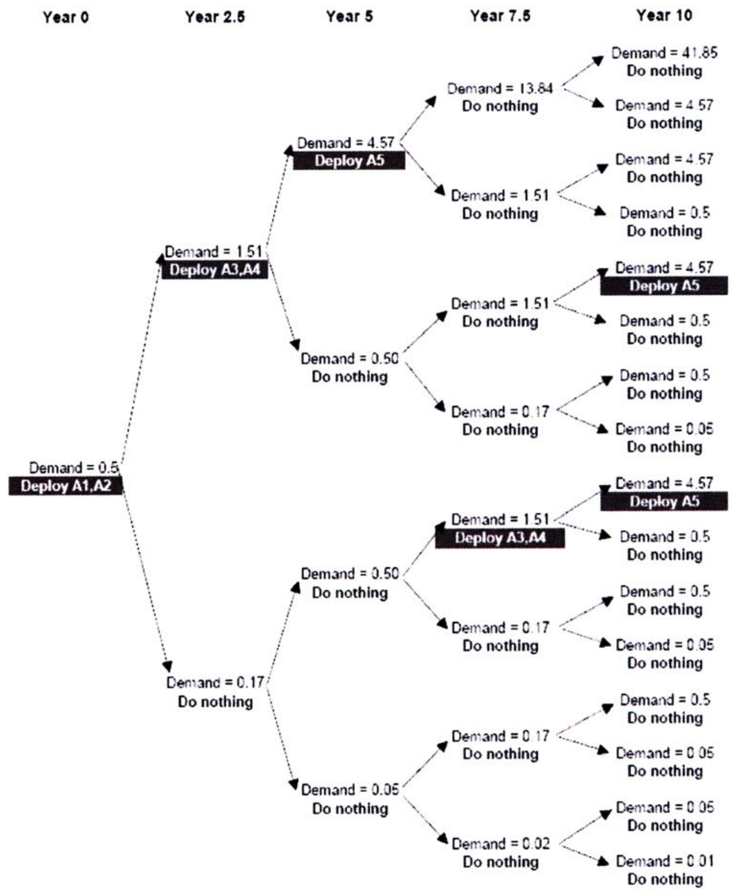


**Figure 35:** A decision tree for contingency development planning for satellite systems
(Figure adapted from Wang, 2005)

Figure 36 shows an example of the iterative decision tree for flexible staged development strategy implemented in Chapter 6. The decision rule determines to build an initial platform with 75% capacity. The expansion of a future stage is based on the reserve estimate. $\Delta(t)$ is the difference between reserve estimate at time t and the amount of reserve being handled by existing platforms. During the each time step of the time window for enabling flexibility (year 3~10), one or two platforms with different capacities will be added depending on which interval that $\Delta(t)$ falls within.

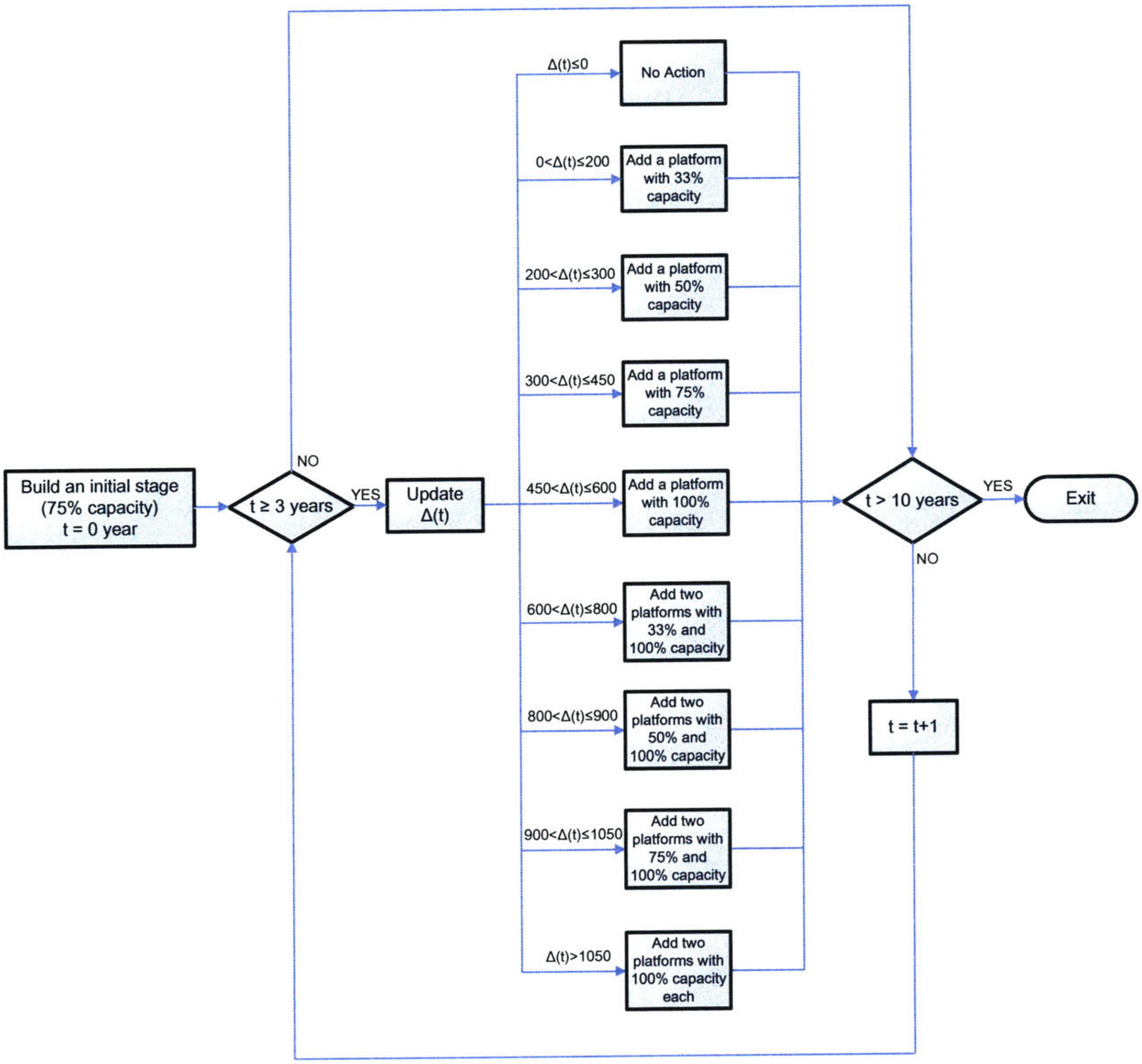


**Figure 36:** An Iterative Decision Tree for the Flexible Staged Deployment Strategy
(The specific decision rule for the flexible staged development strategy in Chapter 6)

## 2) <u>Logical Statement</u>

Similar to decision trees, logical statements, such as If…ELSEIF…THEN…, can be used to represent the decision rules. A decision rule set $\Psi$ can be defined as follows:

A decision rule set $\Psi$ =

{

Take an initial ACTION;

For time $t = n_a$: $n_b$

Update the state vector $\hat{\vec{V}}(t)$ estimate;

IF $C_0\left(\hat{\vec{V}}(t)\right)$ THEN NO ACTION within time step *t*;

ELSEIF $C_1\left(\hat{\vec{V}}(t)\right)$ THEN take *ACTION 1*;

ELSEIF $C_2\left(\hat{\vec{V}}(t)\right)$ THEN take *ACTION 2*;

...

ELSEIF $C_k\left(\hat{\vec{V}}(t)\right)$ THEN take *ACTION k*;

...

ELSEIF $C_m\left(\hat{\vec{V}}(t)\right)$ THEN take *ACTION m*;

END

END

}

where

$n_a$: the starting time step (or the starting year) that action can be taken to exercise build in flexibility (i.e., timing for enabling capacity expansion flexibility).

$n_b$: the end time step (or years) that decisions can be made. $[n_a \; n_b]$ is the time windows for exercising flexibility ($n_a < n_b$).

*m*: the number of action branches (excluding the NO ACTION branch) in each time step.

$$\vec{V}(t) = \begin{bmatrix} \vec{V}_1(t) \\ \vec{V}_2(t) \end{bmatrix} \quad \text{[Eq. 3 - 18]}$$

$\vec{V}(t)$ is a state vector which includes two parts: $\vec{V}_1(t)$ is the state vector for uncertain variables, such as reserve estimate $reserve(t)$ and crude oil price $P(t)$, the other is the system architecture/design state vector $\vec{V}_2(t)$, which includes the system's current capacity, configurations (e.g., number of tieback fields for a hydrocarbon basin). $\hat{\vec{V}}(t)$ is the estimate of the state vector $\vec{V}(t)$, Decision rules triggered actions are based on the estimated state vector $\hat{\vec{V}}(t)$ instead of the true underling state vector $\vec{V}(t)$.

$C_k\left(\hat{\vec{V}}(t)\right)$: the condition is a function of the estimated state vector $\hat{\vec{V}}(t)$, where $k = 1{\sim}m$.

*ACTION k*: the actions of exercising different types of flexibility, where $k = 1{\sim}m$.

The decision rule set $\Psi$ pre-defines a set of conditions and action branches. However, the conditions ($C_k(\vec{V}(t))$), the number of branches ($m$), the timing of exercising flexibility ($n_a$, $n_b$) depend on the specific case. Setting up an initial decision rule will require engineering experience and a set of test runs. The screening model provides a computational lab to experiment and fine tune these decision rules. The conditions in the decision rule are functions of the state vector estimated by decision makers, and the estimate of the state vector evolution over time. So, decision rules provide a way to simulate possible decisions to be taken as human perception of uncertain variables changes over time.

### 3) Decision Networks

Figure 37 shows a Time-expended Decision Network (TDN) for evolving system architectures over time. In this figure, chance nodes are represented as circles and decision nodes are shown as squares.

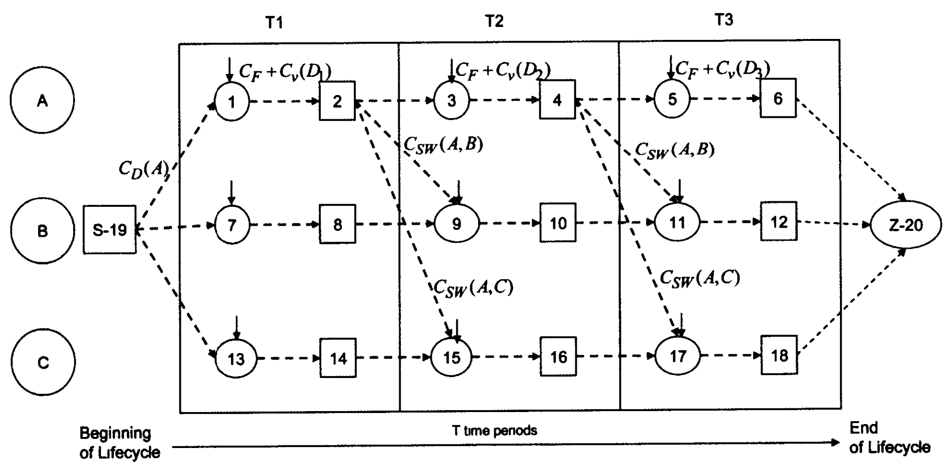


**Figure 37:** Time-expanded Decision Network
(Figure is adapted from Silver and de Weck, 2007)

Figure 38 shows a network representation for the architecture of a hydrocarbon basin. In this network representation, facilities and reservoirs are represented as two types of nodes; the connections between reservoirs and facilities are represented as links.

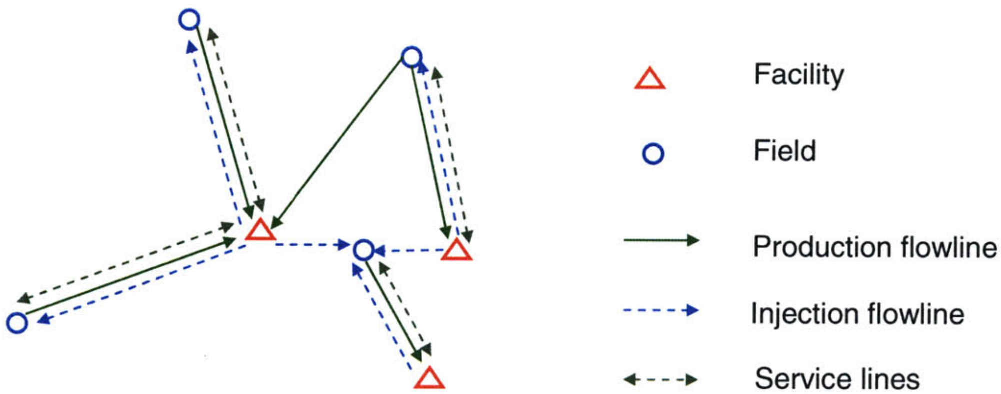


**Figure 38:** Network representation for the architecture of a hydrocarbon basin

The network representation allows system architects to visualize the evolution of field architectures over time and the associated decisions for evolving the architectures. Decision rules determine how field architectures or operations should adapt as uncertainty unfolds. In general, there are two different types of flexibility over the lifecycle of systems: architectural flexibility and operational flexibility. Architectural flexibility is achieved by allowing systems' configurations to adapt to future uncertainty. Operational flexibility is achieved by designs which enable changes in the mode of operations for systems in order to maximize value. In this section, we use development of an offshore hydrocarbon basin as an example to illustrate these two types of flexibility.

Figure 38 shows a network representation of the architecture for a hydrocarbon basin, where facilities (i.e., production or well platforms) and fields (i.e., hydrocarbon fields) are interconnected by flowlines (i.e., production, injection, service, and export flowlines).

**Architectural flexibility**

Architecture flexibility means the flexibility to modify system configurations, layouts, or system designs. Given the network representation of a hydrocarbon basin in Figure 38, architectural flexibility means the ability to

- Add, delete nodes or connections: For the development of a hydrocarbon basin, this type of flexibility implies that facilities, fields, and flowlines can be easily added and abandoned over the lifecycle of projects. Exercising this type of flexibility changes the physical configurations (i.e., the number of fields and facilities, connections) of a hydrocarbon basin.
- Modify connections among nodes: For a hydrocarbon basin development, this means the flexibility to modify the fields-facilities connections, such as tieback of a new field to an existing facility using subsea development as we will show in the case study. This type of flexibility is commonly referred to as a systems' reconfigurability.
- Modify the designs or properties of nodes or connections: This type of flexibility does not change the configuration of a network but the properties of individual nodes or connections can be modified. For example, *Capacity flexibility* allows easy expansion or contraction of the capacity of facilities or flowlines. But, if flexibility is not initially planned or designed into systems, it may be prohibitively costly to change capacity afterwards. For an offshore oil platform, it may be impossible to add additional processing equipment on a platform due to limited space or insufficient sub-structural support.

**Operational flexibility**

Operational flexibility allows easy modification of systems' operation strategies without changing the system's architecture. With operational flexibility, operators can change and fine-tune systems' operations to maximize their value according to current or near-term conditions. Given the long operating stage of capital-intensive projects, operational flexibility can add a lot of value to systems' owners. For example, *capacity allocation flexibility* is one type of operational flexibility, which allocates production capacity for multiple products or resources to maximize production under uncertainty.

Architectural flexibility has long term impact and it is considered strategic flexibility. Operational flexibility focuses on the near term. In some situations, architectural flexibility enables operational flexibility. For example, in the development of a deepwater hydrocarbon basin, tieback flexibility enables the flexibility to allocate production capacity among multiple fields.

An intelligent decision rule has the ability to learn from new information as well as from previous mistakes in the decision making, and it can modify initial decision rules to better adapt to future uncertainties. An intelligent decision rule recognizes the possibility of future changes and provides mechanisms to explore the decision space and then direct the course of actions to more favorable directions. This thesis proposes a simulation approach to explore decision rules and then to screen promising development strategies under uncertainties.

**Experiment and fine tune decision rules**

Figure 39 illustrates the two-phase processes for Systems' design. There is a screening phase and a design phase. The screening phase is to explore and screen promising strategies under multi-domain uncertainties. The design phase is to conduct detailed technical design and economic evaluation of the identified strategies. The thesis focuses on developing methods and tools for the screening phase.

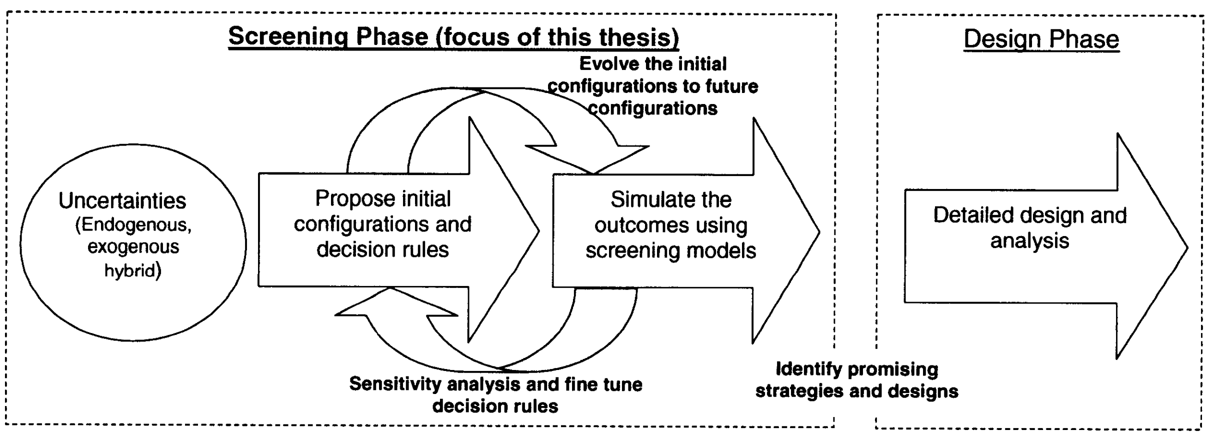


**Figure 39:** Two-Phase Processes for Systems' Design

In the screening phase, the first step is to propose one or several initial configurations and decision rules to determine how to exercise built-in flexibility as uncertainty unfolds. The second step is to simulate these designs and development strategies using screening models. Based on the simulation results, we can fine tune the decision rules by trial and error or sensitivity analysis.

In this thesis, we do not attempt to optimize decision rules. An initial decision rule is based on engineering experience or several simulation experiments. Once an initial decision rule set is available, we can conduct global sensitivity analysis: vary the key parameters of decision rules (e.g., timing of enabling flexibility, number of action branches, and conditions for the action branches) and observe how the outcomes (e.g., VARG curves) change. In this way, we can improve the decision rules by modifying their structure and selecting appropriate values for the parameters in the decision rules. It is future work to apply more sophisticated methods or algorithms (i.e., statistical methods or heuristic optimization) to explore and design "optimal" decision rules. A good decision rule should be able to adaptively shape the distributions of outcomes (e.g., reducing downside tail, extending upside tail).

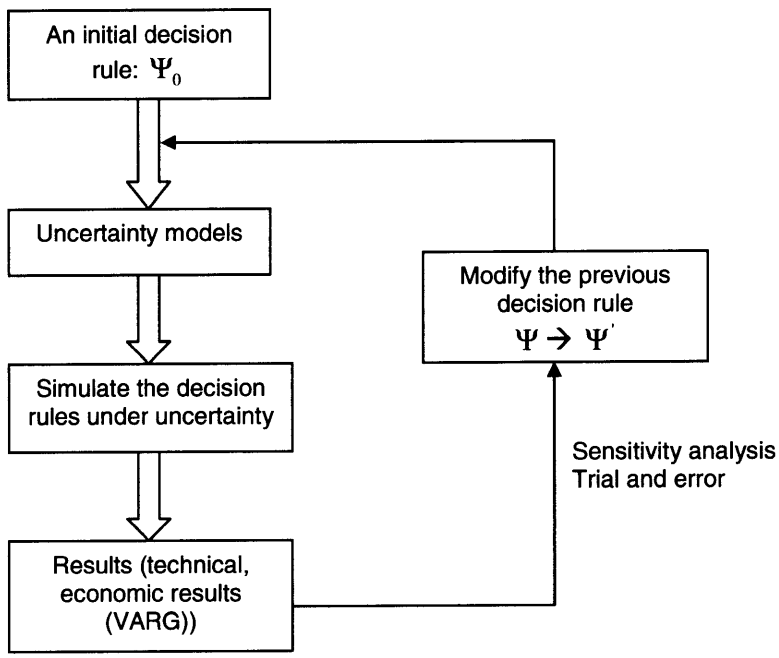


**Figure 40:** Modify an initial decision rule set via trial and error or sensitivity analysis

Consider offshore oilfield development as an example to explain these two stages in the screening phase. The decisions to be made in the field development planning stages are:

- Field Architectures: number of fields/facilities and their connectivity, decisions on staged development, decisions on tieback, subsea architectures, etc.
- Facilities design: oil/gas/water throughputs, number of producers/injectors, wells' locations, spare capacity, facility upgradeability.

Even in the fields' operation and abandonment stages, decisions have to be made in following aspects, such as:

- Field and facilities' operations: adjust daily/monthly production and injection rates, switch between producers and injectors, facility debottlenecking (i.e., add additional processing trains, gas compressors, and pumps for water injection).
- Modification or upgrade of field architectures: add platforms, drill additional producers or injectors, tieback reservoirs to existing facilities.
- Field abandonment: technical and economic conditions for field abandonment, decisions on facility re-use and recycling.

Given the multi-level decisions in offshore oilfield development, it is very challenging for decision makers and system architects to identify "the optimal" strategy from the large number of possibilities. It is even more difficult to define the "the optimal" strategy as the future is unknown. The optimal strategy under a fixed projection of the future may turn out to be sub-optimal. Once committed to a fixed field development plan, it is generally prohibitively costly or even impossible to change the system's architectures or field operations. Because of the irreversible nature of capital-intensive projects, it is essential to explore different strategies under uncertainty, and to identify the most promising strategies (i.e., with built-in flexibilities at multiple levels). Decision rules govern how to change the system architectures, and field operations as uncertainties evolve. In other words, decision rules determine when and how to exercise built-in flexibilities.

## 3.4 A Simulation Framework for Screening Flexible Strategies

This thesis develops a simulation framework to integrate multi-domain uncertainties, decision making, screening models and flexible strategies together. Figure 41 shows the integrated simulation framework. There are two iteration loops. The outer loop is a Monte Carlo simulation loop and each sample includes an instance of the multi-domain uncertainties. The inner loop is the simulation run time iteration, which simulates the development and operation of engineering systems over their lifecycle. There is a decision making module built into the inner loop, which monitors the evolution of multi-domain uncertainty and then modifies the integrated system model or exercises built-in flexibilities if conditions are satisfied. So, since the screening models are essentially time-varying, the model of resource systems can be updated when more information is available, and design and development of technical systems can be changed over the project's lifecycle. After the completion of the simulation, different strategies and their designs are compared in terms of the probability distribution of economic metrics, such as various metrics read from Value-at-Risk-Gain (VARG) curves such as the projects' expected NPV.

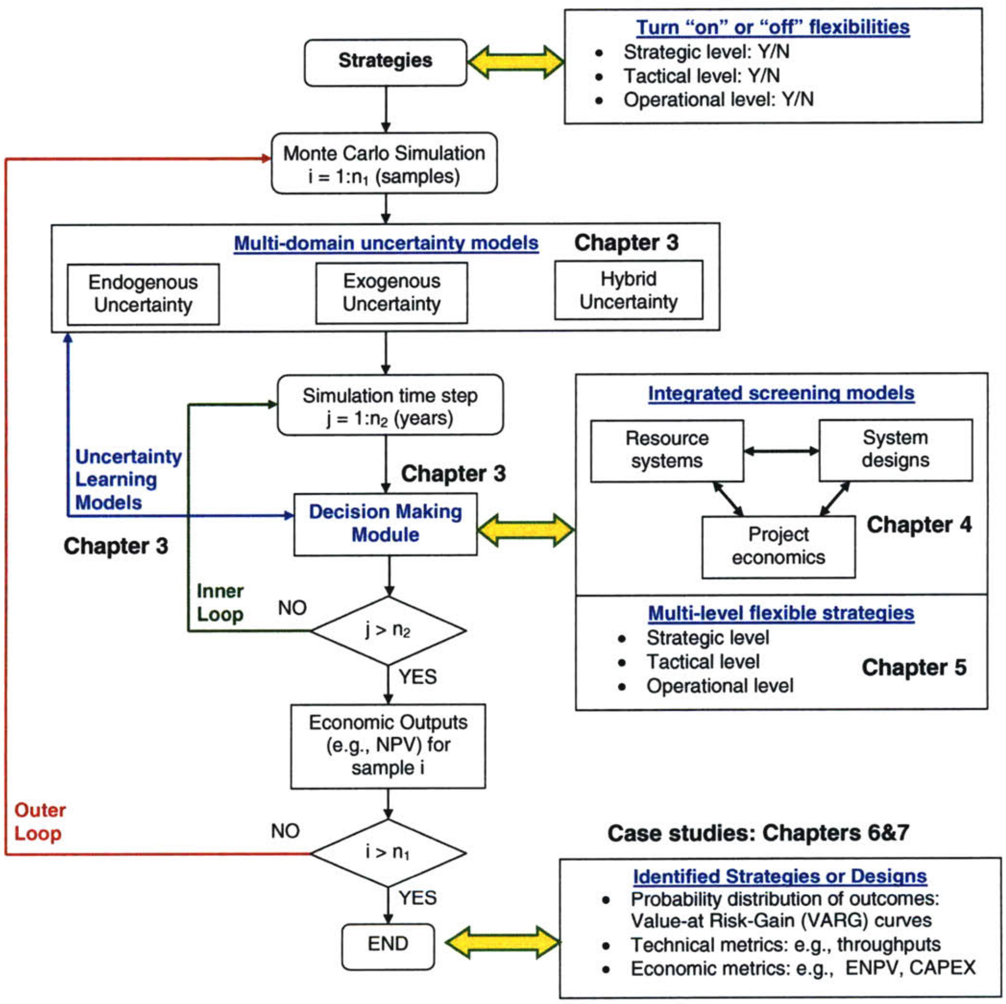


**Figure 41:** A simulation framework for screening strategies under multi-domain uncertainty

A VARG curve is a cumulative distribution of NPV. A good strategy should be able to "shape" the VARG curve in a favorable direction. For example, Figure 42 shows two VARG curves for strategies A and B. The VARG curve for strategy B has a narrower distribution: greater Value at Risk but also lower Value at Gain. The outputs give decision makers and system architects a quantitative way to assess and compare different strategies under uncertainty.

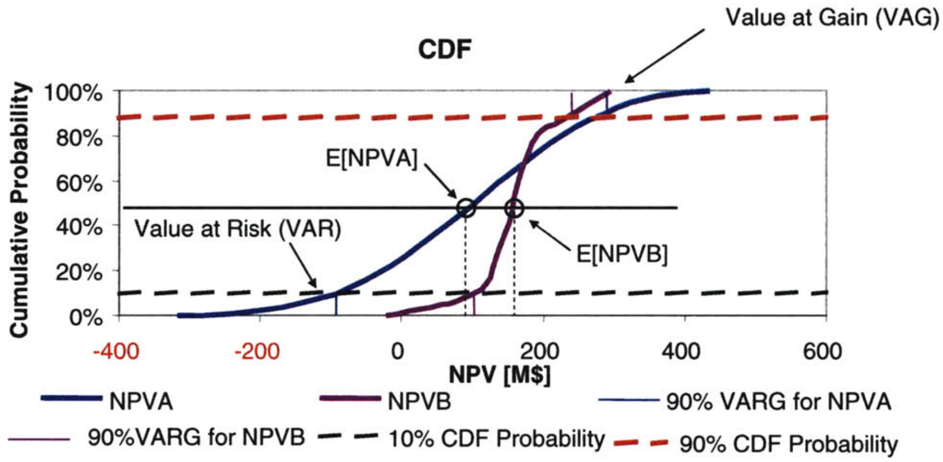


**Figure 42:** Examples of Value-at-Risk-Gain curves

In summary, this chapter develops stochastic models for multi-domain uncertainty and proposes generic ways of representing decision rules for flexible strategies. In particular, a stochastic model has been originally developed in this thesis to simulate how the reserve estimates evolve over time. This model has the potential to represent other types of epistemic uncertainty. Chapter 4 will focus on development of integrated screening models, which interconnect resource systems, technical system designs, and project economics. Chapter 5 will identify and discuss the multi-level flexibilities in engineering systems. Finally, the integrated simulation framework will be applied to offshore petroleum projects through two case studies in Chapters 6 and 7.

# Chapter 4: A Screening Model

## *4.1 Introduction*

A screening model is a concept originally proposed by Wang (2005) to identify real options "in" engineering systems. The screening model is defined as a simplified, conceptual, low- to mid-fidelity model of the system. It is established to screen for the most important variables, uncertain factors, and flexibilities in the system's conceptual and development planning stages. The screening model captures the essential variables and their interactions. From the design space perspective, we can think of the use of a screening model as the first step of a process to reduce the design space of the system. Compared to the high-fidelity model, a screening model is relatively easy to set up and requires less computation time; thus it can be run many times to evaluate different design strategies (with different built-in flexibilities) under uncertainty. The screening model is a first-cut analysis which focuses on identifying important issues, such as important uncertain factors and types of flexibilities in a system's design and operation. Following after the screening phase, a simulation model is applied to conduct detailed engineering design and economic evaluation. The simulation model is a complete and high-fidelity model. The main purpose of the second phase is to examine, under technical and economic uncertainty, the robustness and reliability of the designs, as well as their expected benefits. Figure 43 (a) shows the tradeoff between computational time and model fidelity, and Figure 43 (b) shows the tradeoff between model setup (and data transfer and processing) time and the level of model integration. The comparisons shown in Figure 43 illustrate the following points:

1) Compared to high-fidelity models, mid-fidelity model significantly reduce (on the order of 1000 times less) the computation time. Each run for a high-fidelity model may take hours or even days of computational time on a desktop PC, however, a mid-fidelity model only takes seconds or minutes for each run. Thus, it is not practical to use high-fidelity models to run large numbers of Monte Carlo simulations and to evaluate designs under uncertainty during a project's early stages. In the oil and gas industry, time

pressure during project's appraisal to define stages precludes engineers to explore the large design space and evaluate many designs under uncertainty using high-fidelity models. Thus, only a few deterministic designs can typically be generated and evaluated, which potentially leaves a significant amount of value un-exploited. However, mid-fidelity models are computational efficient and can be used to quickly explore the design space and to screen out promising design alternatives under multi-domain uncertainty during the early stages of projects.

2) For complex systems involving multiple disciplines, the model setup time and data transfer and process time can account for up to 2/3 (according to the author's informal survey in a major oil company) of a modeling engineer's time. Therefore, beside computational time reduction, another important advantage of a mid-fidelity screening model comes from the high level of model integration. A screening model captures the feed forward and feedback flows among multiple domains in an integrated fashion and automates the simulation flows among the models in the sub-discipline, thus, it reduces the time and minimizes potential human errors during model setup and data transfer processes.

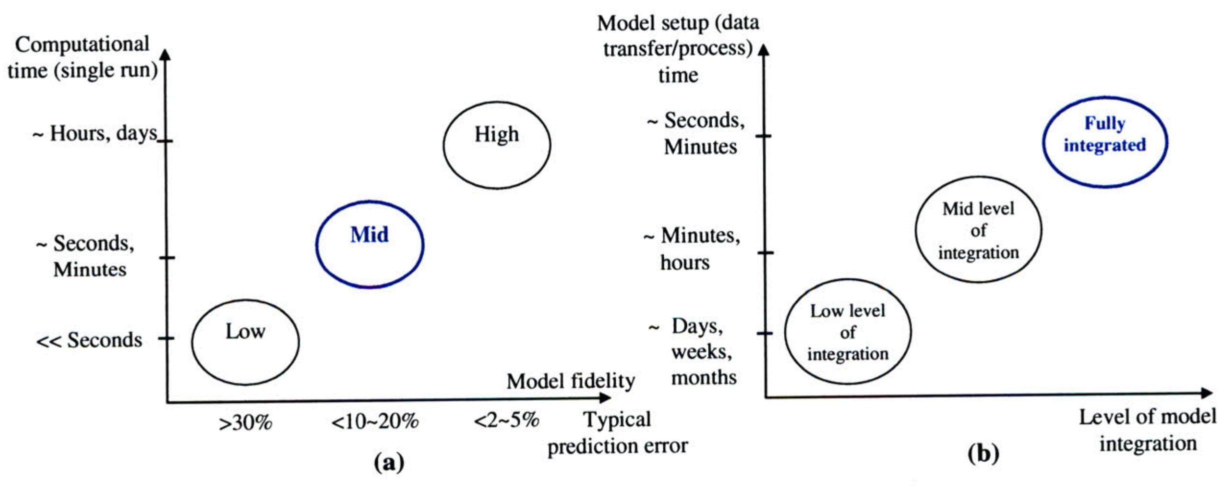


**Figure 43:** (a) Tradeoff between model fidelity and computational time, (b) Tradeoff between level of model integration and model setup time

Therefore, the integrated mid-fidelity modeling approach is suitable for exploring designs under uncertainty. Although Wang and de Neufville (2006) propose and demonstrate the use of screening models to explore flexible designs under uncertainty, there are several limitations in their paper: First the screening model in their paper is a low-fidelity nonlinear programming model. Secondly the uncertain variables are assumed taking several discrete values instead of full probability distributions. Thirdly, the screening model is only used to identify key uncertain variables, and does not provide a systematic framework for how to develop and apply screening models for exploring and evaluating different types of flexibility in engineering systems. Building on the existing literature, this chapter will further develop the concept of using mid-fidelity screening modes to explore flexible development strategies under uncertainty. Furthermore, this chapter demonstrates this approach by developing a mid-fidelity screening model for offshore petroleum projects.

## 4.2 Model Fidelity

Any mathematical or computational model is an abstract representation of reality. Some of these models are high-fidelity, capturing the physics of the systems (e.g., aerodynamic model for aircraft); others are low-fidelity, not explicitly capturing any physics of the systems (e.g., response surface model for representing system input and output relations). Between these two categories, there are mid-fidelity models, which retain some of the physics but in a simplified and computationally efficient way, such as a beam model for an automotive structure or a "tank" model for a reservoir. Modeling of complex engineering systems generally requires models for sub-domains, such as natural resources, technical design, and economic evaluation. The degree of integration among the models of the sub-domains is another dimension to consider for model development. There is a possible scenario in which the models in each sub-domain are high-fidelity but the level of integration is low. For example, in the petroleum industry, high-fidelity models have been developed and applied to reservoirs, facility design, and economic evaluation, but the integration among them is still in practice heavily reliant on human interactions, and this simplification of interfaces has the potential to undermine the model fidelity in the individual domains. In contrast, the models for many aerospace systems are both high-fidelity and highly integrated. Multi-disciplinary design optimization, which integrates aerodynamics, structure, and control, has become very mature for aerospace system design and development (AIAA MDO white paper, 1991). This is partially driven by the fact that any failure of the sub-domains has the potential to cause malfunction of the entire system, which can cause loss of systems and human lives (e.g., the crash of NASA's Columbia space shuttle in 2002, which involved a system failure). The high-stakes situation in the aerospace industry fosters a higher level of model integration.

Figure 44 illustrates the conceptual model for model fidelity and degree of integration. In the remainder of this section, we will differentiate models in terms of fidelity and level of integration. This chapter will provide a rationale for a screening model -- an integrated model at the mid-fidelity level –for decision makers and system architects.

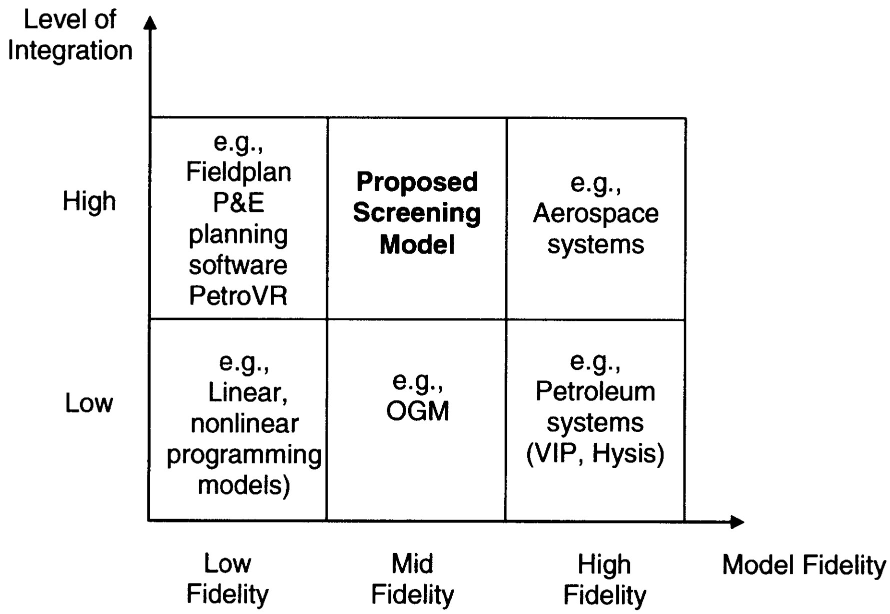


**Figure 44:** Model fidelity and level of integration

### 4.2.1 Low-fidelity Model

A low-fidelity model is a simple representation of a system, and usually it does not capture any physics of the system explicitly. For reservoir systems, statistical approximation of the reservoir modeling workflow based on experimental design theory has been proposed in the literature (Zabalza-Mezghani *et al.,* 2004) For example, a reservoir production response *Prod*(t) (e.g., cumulative oil production, recovery factor, gas-oil ratio) can be expressed as a function of several reservoir characteristics or production variables denoted by $x_1, x_2, \ldots, x_n$ as shown in Equation 4-1:

$$Prod(t) = f(x_1 \quad x_2 \quad \cdots \quad x_n) \qquad \text{[Eq. 4- 1]}$$

Where $x_i$, $i \sim [1\ n]$ represents physical or production parameters for a reservoir. The reservoir characteristics may include: reservoir volume (e.g., STOOIP), pressure, initial oil/gas/water saturation, porosity, permeability, etc. The production variables may include platform production capacity, number of producers or injectors, well productivity, facility utilization, etc.

Experimental design is used to determine the function *f* based on physics-based models, and experimental design allows to:

- Identify the variables that have a large influence on the production response *Prod*(t). This step eliminates variables that have negligible impact on the response and to focus on the important ones.
- Develop a proxy model (e.g., response surface, regression model), which links the production response *Prod*(t) to the influential variables.

Generally, a polynomial model is sufficient to capture the production response behavior as a function of the reservoir characteristics and production variables:

$$Prod(t) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_{12} x_1 x_2 + \ldots \beta_n x_n \qquad \text{[Eq. 4- 2]}$$

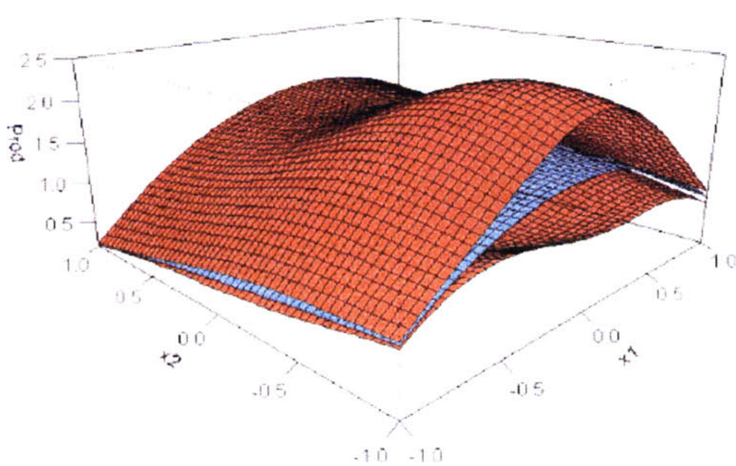


**Figure 45:** A response surface for production
(Figure is adapted from Zabalza-Mezghani, *et al.*, 2004)

Essentially, Equation 4-2 is a response surface for the production profile. The coefficients in Equation 4-2 are the outcomes of experimental design (e.g., response surface, regression model), and it is a surrogate for reservoir fluid flow simulators. Compared to the full-physics reservoir model (millions of grids, partial differential equations for flow simulation), the production response surface model is very computationally efficient. It can be used to predict production profiles given different conditions. Figure 45 shows a production response surface.

A low-fidelity model can be at either a low or a high level of integration. A low-fidelity production profile generator can be highly integrated with facility design and project economics. For example, Equation 4-2 for a production profile takes into account constraints of facility capacity and economic conditions (e.g., field abandonment conditions).

### 4.2.2 High-fidelity Model

Compared to a low-fidelity model, a high-fidelity model represents the physics in the engineering system in great detail. Many engineering domain-specific software tools can be grouped into this category. Computer Aided Engineering (CAE) models of physical systems using computation, mathematics, and graphical visualization. Computer Aided Design and Manufacturing (CAD and CAM) have created a virtual environment for designing and manufacturing mechanical and electronic systems. In the petroleum industry, various software tools have been developed to assist decision making in field development, facility design, and project investment.

- Reservoir Simulators: Commercial (e.g., VIP from Halliburton, ECLIPSE from Schlumberger) or proprietary (e.g., ExxonMobil's EMpower) reservoir simulators are high-fidelity models for subsurface representation, which discretize reservoirs into millions of grid boxes and describe multi-phase flow behaviors using physics principles (i.e., conservation of mass, Darcy equations, isothermal compressibility), and simulate flow rates by solving the finite differential equations. Depending on the complexity of the reservoir and the resolution of each grid box, each simulation run over the field's lifecycle may take a few hours to a few days; thus, only a few reservoir scenarios can be considered, given the time and resource constraints during field appraise, define, and select stages. Monte Carlo simulation based on high-fidelity reservoir models is too computationally intensive to be used in practice. Furthermore, the reservoir modeling and simulation are generally decoupled (or weakly coupled) from the facility design. In practice, some sort of simplification (i.e., coarse gridding, decline curve, material balance) has to be applied to reduce computational time for large numbers of simulations.

- Facility modeling and simulation: Commercial software, such as Aspen Hysis and Oil & Gas Manager (OGM), has been developed for field development planning, facility design modeling, and process modeling. Compared to Aspen Hysis, OGM is at the mid-fidelity level. However, we group these two as high-fidelity facility models because significant engineering time is still required to setup and calibrate the models in contrast to the integrated mid-fidelity model developed in this thesis. These facility and process modeling tools allow designing field development scenarios which may consist of a Central Processing Facility (CPF) (e.g., steel-piled-jacket platform, floating production platform), subsea wells, manifolds, pipelines, etc. Given a field development scenario, this kind of software is able to estimate the costs (i.e., material, procurement, construction, and project management), mass and surface area required for platform, subsea processing equipment, and other infrastructure for field operation. Developing and calibrating a high-fidelity facility or process model would require significant amount of effort from engineers to gather information (i.e., reservoir, technical definition, equipment uses, facility weights and cost inputs) and optimize the facility designs. It is impractical to use high-fidelity facility models to compare a large number of field development alternatives.
- Project economic modeling: Project economic evaluation traditionally is based on spreadsheet models. In recent years, more sophisticated commercial software packages, such as PetroVR, have been developed to integrate Exploration and Production business processes, such as development planning, project scheduling, and economic evaluation. PetroVR has a very detailed representation for project economics (i.e., CAPEX, OPEX, phasing, Production Sharing Agreement, tax regime). It supports probabilistic evaluation of projects under different technical and economic conditions. However, the reservoir and facility representations in PetroVR are low-fidelity and are not at the same level of detail

as the economic model. As a result, the overall fidelity of PetroVR is low although it has a high level of integration.

### 4.2.3 The Need for an Integrated Mid-fidelity Model – A Screening Model

A screening model in this thesis is defined as an integrated model at the mid-fidelity level as shown in Figure 44. To effectively explore the design space during a systems' architectural design and development planning stages, a screening model is necessary for the following reasons:

- The availability of information (i.e., technical and economic information) in the early stages of a system's design and planning is very limited, yet important decisions need to be made. Waiting for more information for developing high-fidelity models will potentially lead to missed business opportunities, delay first oil, and destroy project value. Also, using incomplete and inaccurate information to construct high-fidelity models may give misleading results. A high-fidelity model does not necessarily provide high-fidelity results. Quality of inputs and assumptions for model development all matter.
- Furthermore, uncertain factors persist while decisions need to be made in systems' early design and development planning stages. A tailored high-fidelity model based on the initial best estimate may turn out to be irrelevant. It is unwise to spend a lot of effort to develop a point-optimal solution while uncertainties are high. However, a mid-fidelity modeling approach recognizes the possible changes of assumptions and inputs, and it is easier to make future changes in mid-fidelity models (due to less complexity) than a fully customized high-fidelity model.
- A high-fidelity model generally is computationally intensive and requires manual processes to transfer inputs and outputs between sub-domains' software and tools. It is not convenient to explore a large number of design alternatives in this way. The amount of effort and time required (to interconnect high-fidelity models and simulate with them under uncertainty) can be prohibitive.
- At the other extreme, a low-fidelity model may not retain the necessary technical and economic detail to allow sound engineering and business judgment to play a role in systems' design and development planning. The low-fidelity model takes almost no

computational resources to perform a single run and is easy to set up. Therefore it can quickly examine thousands of design alternatives under uncertainty. However, the results may be misleading due to over-simplification of the technical-economic systems. For example, a low-fidelity reservoir model (such as a response function shown in Equation 4-2) does not capture the true reservoir dynamics. Although the reservoir response function may fit very well (such as reservoir drive mechanism), it may become completely irrelevant if the assumptions and field operating conditions change significantly in the future. Furthermore, a low-fidelity reservoir model is based on the initial field development plan or architecture, thus, the response function is no longer useful if the field architecture evolves (e.g., adds more capacity, ties back other fields) outside the operating boundaries of the initial model.

- An integrated mid-fidelity model is more appropriate for decision makers and system architects in early design and development planning stages. A mid-fidelity model is defined at the level of detail, which retains the essential technical-economic elements and their interactions in a simplified way. The "right" level of detail for a mid-fidelity model can be defined as just at the level of detail where the rank order of different strategies remains relatively stable when the parametric assumptions are within certain ranges. In practice, the mid-fidelity model is developed based on engineers' experiences (e.g., identify the key subsystems and their variables) and quantitative approaches (e.g., Design of Experiments to identify and assess the critical factors). Based on the author's experience, the development of an integrated mid-fidelity modeling tool for petroleum projects requires 6~12 man month's full time work assuming that basic domain knowledge and the model programming skills have been acquired. However, once the tool is built, it only takes a few days or weeks to develop a screening model for new development cases once essential information is available.

The next section will describe a generic representation of a screening model.

## 4.3 A Generic Representation of a Screening Model

A generic integrated systems model for "production systems" is proposed in this section. Production systems take inputs (such as material, energy, information) and transform them into value-added outputs. Figure 46 shows the conceptual structure for this model. There are three types of subsystems in this model, namely the input systems, production systems, and output systems. These three subsystems are connected by generic feed forwards and feedbacks.

Input systems can be interpreted as resources feeding into the production systems. They provide the necessary elements for production. For example, in oil and gas systems, the key input system is the reservoir, which provides reservoir fluids for production. In manufacturing systems, these input systems may include raw materials, supplied parts, labor, energy, etc.

Production systems are the value-adding elements, which transform inputs into outputs. For example, in petroleum systems, the production systems include production/injection wells, platforms, equipment, subsea processing systems, manifolds, pipelines, etc. The equipment and associated processes extract and gather reservoir fluids, and then separate them into streams of hydrocarbons (e.g., crude oil , natural gas) to be further refined. In manufacturing systems, production systems may include plants, assembly lines, factory equipment, processes, workers, etc., which collectively transform raw materials into products for markets.

Output systems are the final "products" of the integrated system model. For petroleum systems and manufacturing systems, crude oil, gas, and consumer products are the outputs. We can also represent outputs in the form of monetary flows, which can be described as economic metrics such as cash flow. Net Present Value (NPV) is determined by cash flows, such as Revenue income, Capital Expenditure (CAPEX), Operating Expenditure (OPEX), etc.

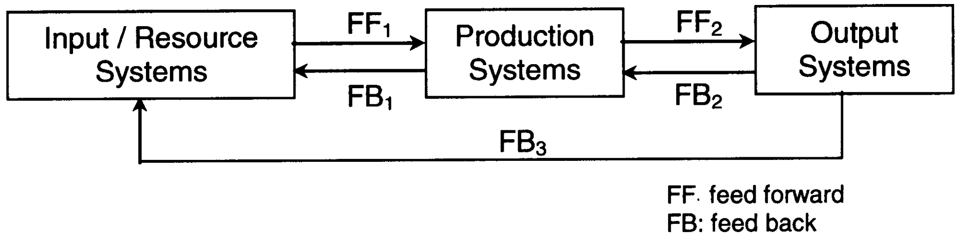


**Figure 46:** A generic integrated screening model

The integration of the systems model is shown in terms of the connections among the three subsystems. There are two types of connections: feed forward and feedback. In general, feed forwards are more intuitive to decision makers and system architects, since feed forward flows generally reflect the sequential material or production flow. Feedbacks are less transparent and may be difficult to identify, especially when these feedbacks span over multiple domains and are separated in time and space. Both the feed forwards and feedbacks can be categorized into physical, logical, and financial flows:

***Physical flows***: Physical flows represent the physical entities going through the entire system. They can be continuous flows such as reservoir fluids in petroleum systems, or discrete flows, such as parts and subassemblies in manufacturing systems. Generally, modeling of physical flows involves quantifying relationships among flow rates. A generic form of this relationship for Figure 46 is shown as follows:

$$q_{FF_2} = f(q_{FF_1} \quad q_{FB_1} \quad q_{FB_2} \quad q_{FB_3}) \qquad \text{[Eq. 4- 3]}$$

where $q$ represents various feed forward and feedback flow rates. Equation 4-3 expresses the output rate of production systems in terms of other feed forward and feedback rates. For example, in a petroleum system, the feed forward flows can be the production fluids (a mix of oil, gas, and water) from reservoirs to production platforms, and then to export systems. The feedback flows can be the produced water and gas injection, which are used to maintain reservoir pressures, from platforms back to reservoirs.

***Logical flows***: Logical flows capture the control logic which regulates the physical flows, such as sequences, timing, and capacity constraints on physical flows. The logical flows are generally represented as a set of potentially time-varying constraints on physical flows. Equation 4-4 gives an example of the inequality constraints on the physical flow rates shown in Figure 46. The first two equations say that the feed forward flows need to be less than the designed capacity. The third equation shows the mass conservation law for the production systems, which means the sum of outflows should be equal to the sum of inflows. The fourth equation shows the dynamic interactions between resource systems and production systems. For example, if the required feedback flows ($q_{FB_1}$) to resource systems are greater than the designed capacity ($q_{cap\_FB_1}$), then feed forward flows need to be reduced accordingly. This is a very common type of constraint for petroleum systems, which balance the production and injection rates between reservoirs and facilities.

$$\begin{cases} q_{FF_1} \leq q_{cap\_FF_1} \\ q_{FF_2} \leq q_{cap\_FF_2} \\ q_{FF_2} + q_{FB_1} = q_{FF_1} + q_{FB_2} \\ if \quad q_{FB_1} \geq q_{cap\_FB_1} \quad then \quad q_{FF_1} \leq q_{cap\_FF_1} \end{cases} \qquad \text{[Eq. 4- 4]}$$

***Financial flows***: Financial flows are monetary flows which are driven by the physical and logical flows. In the feed forward direction, financial flows represent how streams of capital are spent and invested over time and how value is created. In the feedback direction, financial flows represent how the financial gains (e.g., NPV) in the output systems affect the input and production systems. There are several types of feedback flows related to the financial domain:

- Feedback from the financial domain to production systems. For example, if the revenue is less than the operating cost, a production system may be temporarily stopped or permanently abandoned.
- Feedback flows within financial domains. For example, the profit gain may be used to re-invest (shown as extra CAPEX and OPEX flow back to production systems) in the projects, which may improve a project's future cash flows.

In general, the financial flows include streams of cash flows, such as capital expenditures (*CAPEX*), operating costs (*OPEX*), revenue (*R*), *taxes*, etc. *NPV* is widely used to evaluate a project's net value to shareholders based on discounted future cash flows. Equation 4-5 shows a generic formula to calculate project *NPV*. However, Figure 46 does not explicitly show these financial flows.

$$NPV = \sum_{j=1}^{n} \frac{R_j - CAPEX_j - OPEX_j - Tax_j}{(1+r)^j} \qquad \text{[Eq. 4- 5]}$$

where $n$ is the total number of periods, and $r$ is the discount rate.

Capturing of both feed forward and feedback flows among multiple subsystems or domains is a key element that differentiates integrated system models from traditional domain-specific models, which generally have high fidelity within each subsystem but low fidelity in the connections of these subsystems. The integrated model developed in this research is at the mid-fidelity level. A mid-fidelity model is more detailed than a first-order analytical calculation, but less detailed than most domain-specific models. The mid-fidelity model is appropriate for decision making in the early stages of a project. First, a mid-fidelity model is more computationally efficient than domain-specific models, which allow decision makers to explore many design alternatives in an efficient way. Secondly, a computationally efficient mid-fidelity model makes it feasible for decision makers to evaluate and simulate designs under uncertainty. Better informed decisions can be made based on a distribution of possible outcomes. Thirdly, a mid-fidelity model does not require very detailed input. This makes it a more practical modeling approach for projects' early stages while information is incomplete and the environment is highly uncertain. Fourth, a mid-fidelity model captures the basic physics of the systems and the coupling among subsystems; in contrast, a low-fidelity model may give misleading results due to over-simplification.

Conceptually, the proposed integrated systems model is applicable to different industrial infrastructure or production systems. But the instantiations of the model may differ for different types of production systems. Table 11 compares the application of this integrated system modeling approach for petroleum production systems and manufacturing systems.

**Table 11**: Examples of integrated systems model

| | | Petroleum production systems | Manufacturing systems |
|---|---|---|---|
| **Input / Resource systems** | | Hydrocarbon reservoirs | Raw material, labor, energy, engineering designs |
| **Production systems** | | Platform (separation and injection facilities) wells, subsea, pipeline, energy | Plants, equipment, assembly lines, manufacturing and production processes |
| **Output Systems** | | Hydrocarbons (e.g., crude oil, gas) to be refined, emissions (by-products and emissions are also fed into the output system) | Consumer or industrial products to market, market demand, preference |
| **Feed forwards** | **Physical** | Reservoir fluids from reservoir to wells, to platforms, to pipeline, and to export | Parts, subassemblies |
| | **Logical** | Flow rates, pressure control | Demand, throughput, inventory control, production planning |
| | **Financial** | Value added processes, PSA | Value-added processes |
| **Feedbacks** | **Physical** | Re-injection fluids | Re-worked parts or subassemblies |
| | **Logical** | Capacity and drilling constraints on production rates, facility expansion | System's capacity constraints' on throughput |
| | **Financial** | Budget constraint, re-investment, PSA | Budget constraint, re-investment |

Integrated system modeling requires modelers to have knowledge of multiple disciplines and their interactions from a systems perspective. The integration effort required involves the identification of key interactions and understanding of how these interactions affect decision making. The extra effort spent on simplifying the model, and identifying and modeling these couplings in an integrated fashion is worthwhile, especially for decision makers. Not only do these couplings affect the dynamics for the whole system, but they also give decision makers a holistic view to explore a project's alternatives and options, to identity opportunities which may not be obvious in sequential domain-specific models. We therefore hypothesize that modeling the couplings among multiple subsystems and domains in the integrated systems model can lead to better decision making than just relying on discrete domain-specific models. Instead of testing this hypothesis on a generic case, we will demonstrate the value of developing an integrated systems model for decision making on a specific capital-intensive engineering project – an offshore petroleum development. The next section of this chapter will show how to apply this generic integrated systems model to such petroleum projects.

## 4.4 Development of Screening Models for Petroleum E&P Projects

This section applies the integrated systems model structure to an offshore petroleum project and illustrates the processes for modeling the couplings among multiple disciplines at a mid-fidelity level. With the developed integrated systems model, we will show how it can be used as a decision making tool for decision makers and system architects. Petroleum projects involve design and development of complex engineering systems, which require multiple disciplines in the natural sciences, engineering, economics, and social sciences.

1) Natural Sciences: Geology and geophysics: these two disciplines are involved in the early stages of projects, such as the exploration and appraisal stages. Geologists and geophysicists use scientific methods (e.g., seismic, core/log analysis) to understand reservoir structure, and rock and fluid properties, and to estimate reservoir volume and composition. This serves as a critical step for further stages in the project.
2) Petroleum Engineering: Petroleum engineering refers to all engineering disciplines involved in extracting hydrocarbons from the ground, as well as separating and transporting hydrocarbons. Reservoir engineering, in particular, focuses on subsurface engineering design and analysis. For example, through drilling test wells and obtaining samples of reservoir rock and fluids, reservoir engineers work with geologists and geophysicists to conduct experiments and analysis to estimate reservoir volume and composition, and to develop reservoir production plans (e.g., recovery mechanisms). Drilling engineering focuses on efficient production and injection well drilling and well completion design to ensure performance and maintain integrity. Facility engineers design and optimize facilities' designs to minimize costs

and ensure production and integrity. Production engineering manages the interfaces between reservoirs, wells, and surface separation facilities.

3) Project economics: Commercial teams in projects are responsible for the financial aspects of the whole project. Their tasks may include phasing capital investment, estimating operating cost, projecting revenue, and implementing Production Sharing Agreement (PSA) models based on tax regimes in the host country.

4) Social sciences: Petroleum E&P projects also involve social sciences, such as management and political science. Many hydrocarbon resources reside in geopolitically sensitive locations. Decision makers need to consider political issues, and align multiple stakeholders' interests from the beginning of E&P projects to avoid failure in approvals or delays which destroy project value. During the lifecycle of E&P projects, sound management strategies are as important as good technical system design. Also, E&P projects increasingly have a humanitarian role in developing nations. Sometimes, the contract between a host nation and international oil companies requires the development of industrial infrastructure and supply chain capabilities locally, and provides technical training and job opportunities for local people.

Decision making involves the integration of these disciplines. But the integration does not mean to connect these disciplines or domain-specific tools in a sequential way. One common practice is to linearly follow the value chain, for example from geology and geophysics → reservoir engineering → facility engineering → project economics. The main limitation of this linear value chain model is that the potential feedback loops among these disciplines are neglected or over-simplified. Furthermore, uncertain feed forward flows may only be represented by their expected values. Therefore, this work develops an integrated systems model for petroleum projects that captures feedback loops and allows for full uncertainty propagation from one domain to another. Figure 47 shows the screening model structure.

There are three modules in this integrated model: a reservoir module, a facility module, and a project economics module. Compared to the generic model in Figure 46, these three modules correspond to input systems, production systems and output systems respectively. These three modules are coupled by feed forward and feedback flows. The integrated model could contain multiple reservoirs, facilities, and market instances. The integrated systems model developed in the present study was implemented in Matlab with a Graphical User Interface (GUI). The details of the model development are summarized below.

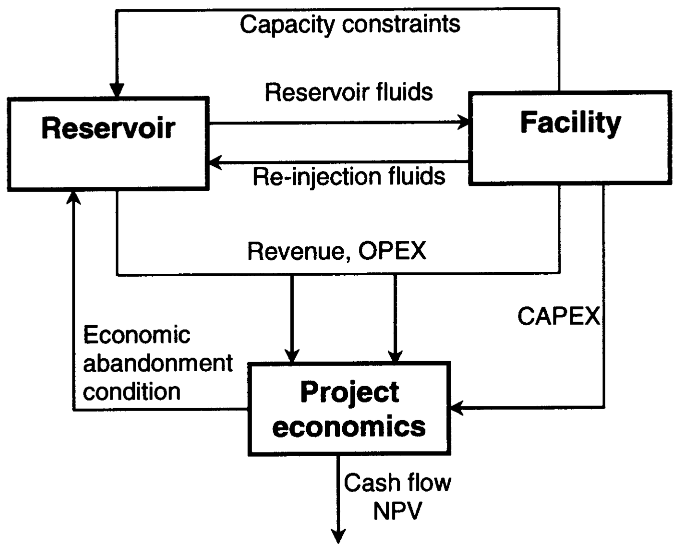


**Figure 47:** Integrated systems model for petroleum Projects

The couplings among reservoirs and facilities are shown in Figure 48. Mixed fluids of oil, gas, and water are extracted from reservoirs and then separated by topside facilities on platforms. Depending on the reservoir operation modes (or drive mechanisms), water, produced gas, sea water, or combinations of them can be re-injected into reservoirs to maintain their pressures. The wells' production rates depend on various physical conditions, such as reservoirs' pressures and fluid compositions. Furthermore, all the production and injection rates are constrained by the capacities of facilities and the ability to drill wells. Therefore, the dynamics of the production systems are very complex due to the various feedback loops and constraints. The following part of this section will describe how to develop simplified reservoir, facilities, and project economics models and how to capture their interactions and constraints.

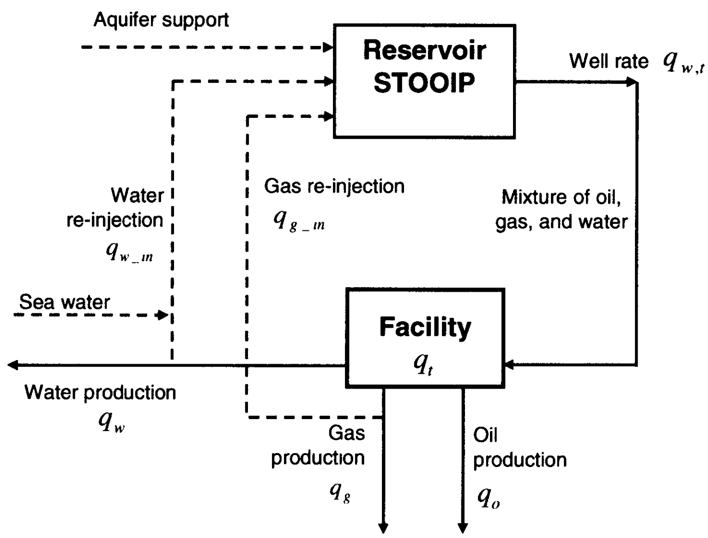


**Figure 48**: Couplings between reservoirs and facilities

### 4.4.1 Reservoir Model

Instead of relying on a high-fidelity 3D reservoir model, we developed a simplified reservoir model based on material balance equations by assuming homogeneity of the reservoir (Lund, 2000). The assumptions for this reservoir model are:

- Homogeneous assumption: It assumes that a reservoir behaves like a homogeneous tank, and any change (i.e., pressure, saturation) will be instantaneously reflected across the entire reservoir. So it is a zero dimensional model and any geographical differences are not explicitly taken into account. (but this model partially accounts for geographical heterogeneity by adding water-oil-ratio and gas-oil-ratio correction coefficients which can be calibrated from a similar high-fidelity reservoir model)
- Reservoir pressure: Reservoir pressure is assumed to remain constant if the injection fluids and gas exactly replace the withdrawal of fluids from the reservoir. For primary depletion (without any injection), the production rate of total fluids is determined by the isothermal compressibility equation (exponentially declines if there are no facility constraints).
- Identical wells: The model assumes that all wells are identical (i.e., same production rate, pressure) and that they are completely connected. So all wells reflect the state of a

reservoir instantaneously and decline in the same manner regardless of when they are brought into stream.

Depending on the reservoir drive mechanisms; the reservoir model developed in this thesis can handle five types of reservoir operations modes:

- Primary depletion: It assumes that there is no water and gas injection. As reservoir fluids are extracted, reservoir pressure declines. Once the bubble point pressure is reached, solution gas starts to become liberated from the oil and since the liberated gas has a high compressibility, the rate of decline of pressure per unit of production slows down. The main drive mechanism is the expansion of remaining fluids and solution gas. In modern oilfields, it is very rare to let reservoir pressure drop below the bubble point pressure because this destroys a reservoir's productivity. Therefore, some kind of reservoir pressure support methods needs to be applied, such as engineered water and gas injection, to increase the recovery factor. Thus, the typical recovery factor from primary depletion is very low, ranging from 5~30%.
- Aquifer drive: Natural water drive occurs when the underlying aquifer is both large and the water is able to flow into the oil column, i.e., it has communication paths and sufficient permeability. With these conditions satisfied, once production from the oil column creates a pressure drop the aquifer responds by expanding, and water moves into the oil column to replace the voidage created by production.
- Engineered water injection: If aquifer support is not available or insufficient, produced water or sea water can be re-injected into reservoirs to maintain pressure. However, this engineered water injection requires facilities, such as injection wells and equipment on platforms, such as water treatment and pumps. For a water drive (natural or engineered) oilfield, the water cut (water cut = water production / (oil + water production)) may exceed 90% in the final part of the field's life. As water cut increases, oil production typically declines; while constant gross liquids production is maintained. High water cut is one reason for field abandonment. The recovery factor is typically in the range of 30% ~ 70%, depending on the strength of the natural aquifer, or the sweep efficiency of injected water.

- Gas gap drive with gas injection: A gas cap may exist in a reservoir as an initial condition. The high compressibility of the gas provides drive energy for production. As production occurs, the gas cap expands and approaches the producing wells. As a result, the effective produced GOR increases. Produced gas maybe re-injected into reservoirs as a way to store or dispose of gas (if no gas export facility is available), or to maintain reservoir pressure. Typical recovery factors for gas cap drive are in the range of 20%~60%.
- Combination drive: It is possible that more than one of these drive mechanisms occur simultaneously. For example, a reservoir can be operated with engineered water and gas injection, which is very common for current oilfield operations. Material balance techniques are applied to historic data to estimate the contribution of each drive mechanism to overall pressure maintenance and hydrocarbon production.

Reservoir dynamic behavior is described by the isothermal compressibility equation:

$$dV = \left[c_o \cdot V_o + c_g \cdot V_g + c_w \cdot V_w\right] \cdot dP \qquad \text{[Eq. 4- 6]}$$

where the subscripts refer to oil, gas, and water, $c_i$ and $V_i$ are the compressibility and volume respectively. The term $dV$ represents the net underground withdrawal of fluids from the reservoir, which may be a mix of oil, gas, and water. When a volume of fluid ($dV$) is removed from the reservoir through production, the resulting drop in pressure ($dP$) will be determined by the compressibility and volume of the remaining components of the reservoir system. Equation 4-6 is one of the fundamental equations governing reservoir dynamic behavior. Depending on different types of reservoir operations modes, Equation 4-6 can have different forms.

Figure 49 illustrates a generic production and injection model for a reservoir. Under the assumptions of a "tank model", a reservoir can be treated as a homogeneous tank filled with a perfect mix of oil, gas, and water in the pore space. The total volume of the space between rock grains is called pore volume. Figure 49 show the pore space as an idealized tank. The production fluids ($q_{prod}$) include a mix of oil, gas, and water according to their saturation in the reservoir conditions. As reservoir fluids are extracted through production, it creates voidage. Thus, three scenarios may happen to replace the empty pore space crated by production: the pore volume may be compressed due to the drop of reservoir pressure; produced water (or sea water) and gas can be re-injected into reservoir to maintain pressure, or natural water (i.e., aquifer) if it exists may flow into the empty pore space created by production.

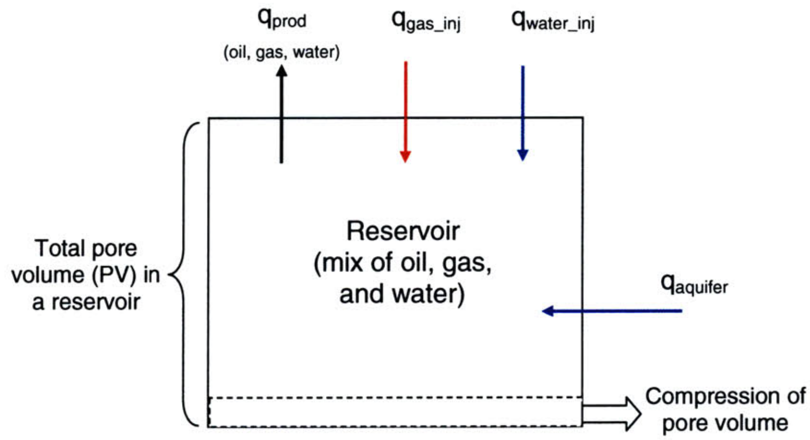


**Figure 49:** A generic production and injection model of a reservoir

A generic material balance equation can be derived from Equation 4-7. it states how reservoir pressure $\Delta p_t$ changes when production and injection occur. The left hand side of the equation includes the response of a reservoir to the production voidage; the right hand side of the equation shows the production of a reservoir.

$$N(B_t - B_{ti}) + G(B_g - B_{gi}) + (NB_{ti} + GB_{gi})\left(\frac{C_f + C_w S_{wi}}{1 - S_{wi}}\right)\Delta p_t + W_e + W_I B_{Iw} + G_I B_{Ig} \quad \text{[Eq. 4- 7]}$$
$$= N_p B_t + N_p (R_p - R_{soi}) B_g + W_p B_w$$

The response of reservoir includes the following components:

1) Expansion of remaining liquids and gas $N(B_t - B_{ti}) + G(B_g - B_{gi})$

where $N$ is the initial oil in place, $B_t$ is the two-phase (liquids with dissolved gas) formation volume factor, $B_{ti}$ is the initial two-phase formation volume factor, $G$ is the initial gas in place, $B_g$ is the gas formation volume factor, $B_{gi}$ is the initial gas formation volume factor, $N(B_t - B_{ti})$ and $G(B_g - B_{gi})$ represents the expansion of remaining fluids and the expansion of the free gas cap respectively as production occurs.

2) Compression of pore volume $(NB_{ti}+GB_{gi})\left(\frac{C_f+C_wS_{wi}}{1-S_{wi}}\right)\Delta p_t$

where $C_f$ is the formation compressibility, $C_w$ is the water isothermal compressibility, $S_{wi}$ is the initial water saturation, $\Delta p_t$ is the reservoir pressure drop during a discrete time interval. The term $(NB_{ti}+GB_{gi})\left(\frac{C_f+C_wS_{wi}}{1-S_{wi}}\right)\Delta p_t$ captures how much pore space is compressed due to the pressure drop $\Delta p_t$.

3) Injection water ($W_I B_{Iw}$), gas ($G_I B_{Ig}$) or natural water (aquifer) support ($W_e$)

where $W_I$ and $G_I$ are the cumulative water and gas injected into the reservoir respectively; $B_{Iw}$ and $B_{Ig}$ is the injected water and gas formation volume factor; $W_e$ is natural water influx into the reservoir. The term $W_e+W_I B_{Iw}+G_I B_{Ig}$ captures the amount of voidage replaced by injections and aquifer support under reservoir conditions.

The right hand side of Equation 4-7 includes the production of a reservoir, which includes the following components:

1) Crude oil production (with associated dissolved gas) $N_p B_t$

where $N_p$ is the cumulative oil produced. $N_p B_t$ computes the produced crude volume (with associated dissolved gas) under reservoir conditions.

2) Produced free gas $N_p(R_p-R_{soi})B_g$

where $R_p$ is the produced gas oil ratio; $R_{soi}$ is the initial solution gas oil ratio. Thus, $N_p(R_p-R_{soi})B_g$ is the produced free gas under reservoir conditions.

3) Produced water $W_p B_w$

where $W_p$ is the cumulative water produced. $W_p B_w$ calculates the produced water under reservoir conditions.

A discrete version of the material balance equation was implemented as a reservoir routine in Matlab. This routine also takes into account capacity constraints of topside facilities. Figure 50 illustrates the flow chart for the reservoir routine. The details of the reservoir model are included in Appendix 1. The simulation flow chart applies to single reservoir and single facility scenario. To tieback multiple reservoirs to a single facility, the constraints become more complex because facility capacities need to be dynamically allocated among multiple reservoirs, which have their own characteristics. In Chapter 7, we will develop a reservoir profile generator for the tieback case study that can handle this situation.

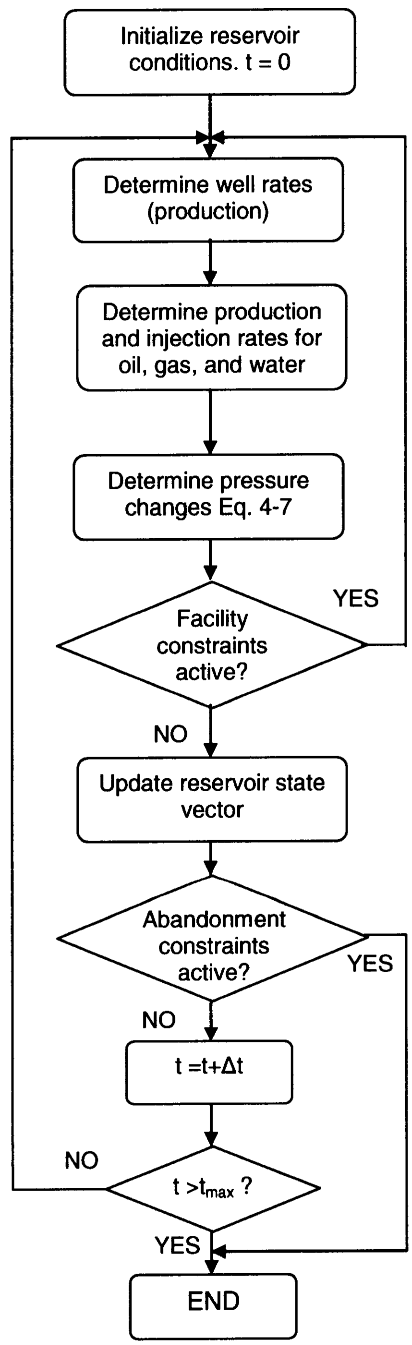


**Figure 50:** Flow chart for reservoir model

In order to validate this model, we applied it to a mature oilfield with 15 years of historical data. In this model, linear or quadratic WOR and GOR correction coefficients are developed to account for heterogeneity of reservoir fluids. The original tank model without any correction assumes the produced water and free gas are proportional to their volumetric percentage in reservoir conditions. However, the three components (i.e., oil, water, and free gas) are not perfectly mixed. Due to gravity, water is on the bottom; oil is in the middle; and the free gas cap usually exists on the top. As a result, the water break through usually happens later as the water-oil contact surface rises during production (and water injection); free gas production occurs as the gas-oil contact drops to a well's bottom hole. The relative production rates of oil, gas, and water are also affected by their relative permeability. By introducing WOR and GOR correction coefficients, it allows the model to adjust the production behavior for water and gas, such as delaying the timing of water breakthrough and free gas production. Figure 51 shows the comparison results between actual and simulated production profiles.

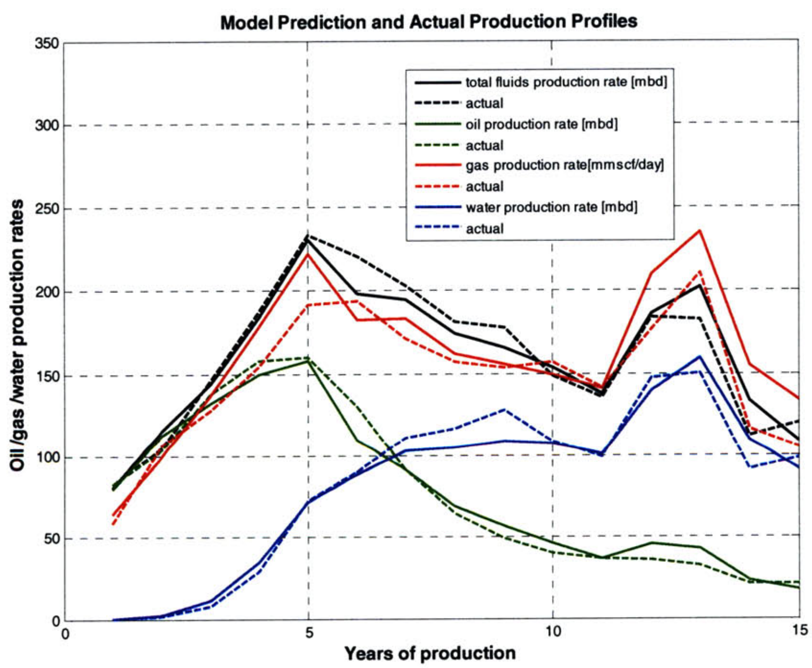


**Figure 51:** Comparisons between reservoir model predictions and actual production and injection profiles

Table 12 compares the errors between model predictions and actual data in terms of dimensionless root mean square and cumulative production errors. The dimensionless root mean square error is defined as the sum of point-to-point errors, and cumulative error is defined as the difference between cumulative production or injection volumes over the field's operation.

$$RMSE^{Dimensionless} = \sqrt{\frac{1}{n}\sum\frac{(simulated_i - actual_i)^2}{actual_i^2}} \quad \text{[Eq. 4- 8]}$$

Where $n = [1, \ldots, 15]$ represents annual average production and injection rates. The simulation model is run with three scenarios: 1) without GOR correction coefficient; 2) with linear GOR correction coefficient; 3) with quadratic GOR correction coefficient. There are several interesting observations from this comparison study: GOR correction coefficients (linear or quadratic) reduce RMSEs, but they do not necessarily reduce cumulative errors. Secondly, the quadratic correction coefficient performs better than the linear one in terms of cumulative error. Finally, a correction coefficient may reduce error for some production rate predictions at the cost of increasing others. For example, compared to no-GOR correction coefficient, the quadratic coefficient reduces oil and gas production errors but increases the error for the water production rate. This can be explained by the Pareto front analogy, in which an optimal point in the Pareto front can not improve a single objective without costing of achieving the other objectives (such as increased error for water injection prediction).

**Table 12:** Comparisons of production or injection errors W/O GOR correction coefficients

| | Dimensionless RMSE (%) | | | Cumulative error (%) | | |
|---|---|---|---|---|---|---|
| | Without GOR cor. coeff. | Linear GOR cor. Coeff. | Quadratic GOR cor. coeff. | Without GOR cor. coeff. | Linear GOR cor. Coeff. | Quadratic GOR cor. coeff. |
| Oil Production | 15.50% | 11.99% | 11.12% | 2.04% | 1.00% | **0.76%** |
| Gas Production | 21.32% | 14.35% | 16.95% | 4.36% | 8.95% | **3.94%** |
| Water Production | 11.73% | 10.27% | 10.90% | 1.07% | 0.11% | **1.53%** |
| Water Injection | 26.39% | 21.78% | 23.75% | 6.62% | 9.15% | **5.66%** |

From this validation case study, the cumulative production or injection errors are less than 10%, which may be within the acceptable range for early design and field development planning. In general, a 10% prediction error is typically associated with a mid-fidelity model. However, this oilfield is in the mature stage with 15 years of production data. We might expect higher errors if this reservoir model were applied in the early production period of an oilfield, but the increased discrepancy might largely originate from uncertainties in the inputs and limited historical data instead of model fidelity. In the early stages of a field development, a high-fidelity model does not necessarily give better results than a mid-fidelity model due to the uncertainties and errors in inputs. Models with different levels of fidelity should be compared with the same inputs at the same time frame. This is one of the directions for future work in integrated system modeling.

Calibrating models against actual data or high-fidelity data (where available) is an important step for the mid-fidelity modeling approach. Calibrating the model and assessing the level of fidelity gives decision makers confidence in the models. However, we should keep a dynamic view of model calibration. The level of confidence of mid-fidelity models can be progressively improved as actual information becomes available. As a rule of thumb, a mid-fidelity model should fall within 10% error of the true values.

### 4.4.2 Facility Model

To develop a hydrocarbon basin, there are many architectures and design alternatives. In general, a facility model includes hierarchical decisions in field design and development:

- Choice of development concepts: This is the highest level decision in the facility model. Depending on a basin's geographical location, environmental condition, and technical constraints, different types of development concepts can be selected. For an offshore oilfield, there are roughly a dozen proven development concepts for supporting topside's processing equipment and supporting utilities, such as Steel Pile Jacket platform (SPJ), Floating, Production, Storage, and Offloading platform (FPSO), Semi-submersible platform, and gravity based platforms. However, the preferred concept is often determined by water depth.

- Field architecture configuration: The field architecture describes how platforms and reservoirs are connected, e.g. through subsea architectures, such as subsea processing systems, wells, manifolds, production and injection pipelines, etc. For a large oilfield, the field architecture also determines how to develop multiple platforms over time. For multiple small oilfields in a basin, the field architecture locates the central production facility, and sets when and how to tieback reservoirs to facilities.
- Facility designs: Facility design is the lowest level decision in the mid-fidelity facility model. The design variables include key throughputs of processing facilities, such as production rates for oil, gas, and water, and injection rates for water and gas.

In this thesis, the facility model essentially quantifies two relationships:

1) the choices of architectures (and designs) and reservoir production dynamics
2) the choices of architectures (and designs) and their costs (i.e., CAPEX, OPEX)

The first relationship has been considered implicitly as a constraint in the reservoir model. So, this section will focus on developing parametric facility cost models. Generally, Capital Expenditure (CAPEX) for an offshore petroleum project is composed of five elements as follows:

$$CAPEX(t) = C_{plat}(t) + C_{well}(t) + C_{surf}(t) + C_{export}(t) + C_{expand}(t) \qquad \text{[Eq. 4- 9]}$$

where $C_{plat}(t)$ is the initial platform (incl. topside and substructure) cost at time t; $C_{well}(t)$ is total well cost at time t; $C_{surf}(t)$ is total cost for Subsea, Umbilical, Riser, and Flowlines (SURF)[10] at time t; $C_{export}(t)$ includes cost of export systems (e.g., export pipeline, storage, offloading, etc); $C_{expand}(t)$ is platform expansion cost at time t.

The initial platform cost includes all costs related to platform design, fabrication, transportation, and installation. It can be phased over a project's initial development period $t_{dev}$, and typically this period can be on the order of 3~5 years. There are two ways to model platform cost: one is

[10] For deepwater oilfield development, SURF cost may account for 35~45% of total CAPEX while well costs may account for 30~45% and platform cost may only account for 20%.

to develop parametric cost models by applying Design of Experiments on higher fidelity facility models such as OGM models. Equation 4-10 shows that platform cost can be expressed as a function of several key design variables and platform type; and the other is to use actual project data to fit a regression model, which actually reduces the level of fidelity of the model. Equation 4-11 shows that platform cost includes a fixed term and a variable term depending on platform capacity, where $b_0^{plat}$, $b_1^{plat}$, and $a^{plat}$ are cost parameters. $a^{plat}$ is usually less than 1 (i.e., 0.6) to reflect economies of scale.

$$\sum_{t=0}^{t_{dev}} C_{plat}(t) = f_{platform\_type}(water\_depth, \quad q_{cap\_oil}, \quad GOR, \quad ...) \qquad \text{[Eq. 4- 10]}$$

$$\sum_{t=0}^{t_{dev}} C_{plat}(t) = b_0^{plat} + b_1^{plat}(q_{cap\_oil})^{a^{plat}} \qquad \text{[Eq. 4- 11]}$$

The well costs include drilling and completion costs for producers and injectors (water injectors or gas injectors). If we assumes that all producers are identical, the well costs (i.e., producer, water or gas injector) can be calculated as the product of the average well cost and number of wells. Equation 4-12 defines well cost, where $fC_{well\_prod}$, $fC_{well\_water\_inj}$, and $fC_{well\_gas\_inj}$ are average cost parameters depending on reservoirs' geological locations, economic conditions, etc. These costs are only incurred during the time period $t$ when the production or injection wells are drilled.

$$C_{well}(t) = fC_{well\_prod} \cdot D_{prod}(t) + fC_{well\_water\_inj} \cdot D_{water\_inj}(t) + fC_{well\_gas\_inj} \cdot D_{gas\_inj}(t)$$

[Eq. 4- 12]

As shown in Equation 4-13, SURF cost is composed of subsea, umbilical, riser, and flowline costs, which are determined by the scale of development, such as lengths and diameters of umbilical and flowlines, numbers of risers, and number of wells. There are parametric cost models for each component of SURF, but these models are program-specific and need to be calibrated for individual projects.

$$C_{surf}(t) = C_{subsea}(t) + C_{umbilical}(t) + C_{riser}(t) + C_{flowline}(t) \qquad \text{[Eq. 4- 13]}$$

Field expansion cost, includes all costs related to field expansion, such as platform expansion ($C_{expand}(t)$), adding additional wells and SURF infrastructure, field expansion cost[11], $C_{expand}(t)$, is shown as follows:

$$C_{expand}(t) = m\left(C_{plat\_\exp}(t) + C_{well\_\exp}(t) + C_{surf\_\exp}(t)\right) \qquad \text{[Eq. 4- 14]}$$

where $C_{plat\_\exp}(t) = b_0^{plat} + b_1^{plat}(q_{cap\_add})^{a^{plat}}$ , $C_{well\_\exp}(t)$ and $C_{surf\_\exp}(t)$ are computed according to Equation 4-13 and 4-14 based on the number of new wells and the expansion of SURF infrastructure.

In the Equation 4-14, $m$ is a cost multiplier and $q_{cap\_add}$ is the increment of platform capacity (such as crude oil production). A flexible strategy (e.g., tieback flexibility, capacity expansion flexibility) usually requires an initial investment (or cost of option $C_{cost\_of\_option}$) to acquire the flexibility, but the actual total cost of acquiring and exercising ($C_{cost\_of\_option} + C_{expand}(t)$) the capacity expansion flexibility may be less expensive than the cost of expansion for an inflexible strategy. This is because the cost multiplier ($m$) for a flexible strategy is smaller than the cost multiplier for an inflexible strategy. Quantifying $m$ in general is left for future work.

### 4.4.3 Project Economics model

Operating Expenditures (OPEX) include fixed OPEX and variable OPEX. Fixed OPEX is proportional to the capital cost of the facilities to be operated and is therefore based as a percentage of the cumulative CAPEX. Variable OPEX is proportional to the production throughput (e.g., oil production) and is therefore related to the production rate. Hence,

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[11] This equation is adapted from a paper by Jablonowski, *et al.*, (2008)

$$OPEX(t) = A \cdot \sum_{t=0}^{t} CAPEX(t) + B \cdot q_o(t) \qquad \text{[Eq. 4- 15]}$$

Where $A$ and $B$ are cost parameters which can be estimated based on historical data of similar fields. $\sum_{t=0}^{t} CAPEX(t)$ is the cumulative CAPEX up to time $t$.

Hydrocarbon resources belong to nations who own the land or offshore shelf. International Oil Companies (IOC) provide technology and services, or operate fields on behalf of shareholders. An economics model determines how to split the revenue or share the capital investment between operating companies and host governments. There are two main types of economics models for petroleum projects: royalty-based economics models and Production Sharing Agreements (PSA).

**Royalty-based economics model**

This fiscal system is set up by the host government (i.e., UK, US), who claims its entitlement to income in the form of tax and royalty.

*Net cash flow for operating company:*

$$NCF(t) = Revenue(t) - OPEX(t) - CAPEX(t) - Royalty(t) - Tax(t) \qquad \text{[Eq. 4- 16]}$$

where revenue is the product of hydrocarbons' prices and total production in time period $t$. The hydrocarbon products include crude oil and natural gas.

$$Revenue(t) = P_{hydrocarbon}(t) \cdot q_{hydrocarbon}(t) \qquad \text{[Eq. 4- 17]}$$

Royalty is normally charged as a percentage of gross revenue from sale of hydrocarbons.

$$Royalty(t) = royalty\_rate \cdot Revenue(t) \qquad \text{[Eq. 4- 18]}$$

Prior to the calculation of tax, we need to calculate fiscal costs, which commonly include the royalty, OPEX, and capital allowances (the amount of capital expenditure deductible from taxable income, i.e., straight line method, declining balance method).

$$Fiscal\_costs(t) = Royalty(t) + OPEX(t) + capital\_allowances(t) \qquad \text{[Eq. 4- 19]}$$

Tax is a percentage of taxable income. Taxable income is the net of revenue after subtraction of fiscal costs. The tax rate may also change over the life of an oilfield, which is another source of uncertainty.

$$Tax(t) = tax\_rate \cdot (Revenue(t) - Fiscal\_costs(t)) \qquad \text{[Eq. 4- 20]}$$

*Net cash flow for host government:*

In royalty-based economic models, host governments do not share any risk of capital investment with operating companies. As long as revenue is positive, the host government gains income. The net cash flow for the host government is royalty plus tax incomes as follows:

$$NCF(t) = Royalty(t) + Tax(t) \qquad \text{[Eq. 4- 21]}$$

**Production Sharing Agreement (PSA)**

The PSA is another prevalent form of fiscal system for petroleum projects. Under a PSA, investors (i.e., IOC) enter into an agreement with the host government to jointly explore, potentially appraise and develop oilfields. The investors form a contract group or joint venture with the host government. Typically, the contract group carries the cost of exploration, appraisal, and development, and later claims these costs from a tranche of the produced oil and gas (called "cost oil"). The remaining volume of production (called "profit oil") is then split between the contractor group and the host government. The sharing percentage of profit oil for the contractor group may be a function of the economic metrics for the contractor group, such as Return On Investment (ROI). For example, if the contract's group' ROI reaches an upper bound, the sharing percentage for profit oil decreases in the next time period. As a result, the PSA limits the upside gain for the contractor group. This is also one of the reasons that some joint ventures' profits are constrained by the PSA "floor" even as the oil price has skyrocketed recently. Oil price inflation also drives the supply chain costs up such that some margins of IOCs could be reduced in some PSAs despite high market prices for hydrocarbon products.

*Net cash flow for a contractor group:*

Net cash flow for a contractor group includes revenues and expenditures as shown in Equation 4-22:

$$NCF(t) = Revenue(t) - OPEX(t) - CAPEX(t) - Tax(t) \qquad \text{[Eq. 4- 22]}$$

Revenue is composed of cost oil and a share of profit oil. The PSA defines how much capital investment can be recovered as a function of CAPEX and timing of investment. The sharing percentage of profit oil is a function of the contractor group's profit. The cost of oil and profit oil is determined by the PSA, which are functions of the contractor group's capital investment and revenue. These functions and dynamic sharing percentages are considered highly confidential and would depend on specific contracts.

$$Revenue(t) = cost\_oil(t) + sharing\_per(t) \cdot profit\_oil(t) \qquad \text{[Eq. 4- 23]}$$

$$Tax(t) = tax\_rate \cdot sharing\_per(t) \cdot profit\_oil(t) \qquad \text{[Eq. 4- 24]}$$

*Net cash flow for a host government:*

Net cash flow for a host government can be computed as follows:

$$NCF(t) = (1 - sharing\_per(t)) \cdot profit\_oil(t) + Tax(t) \qquad \text{[Eq. 4- 25]}$$

One feedback loop from the economic model back to the facilities model is to determine the economic abandonment condition for a declining stage oilfield. Beside other technical conditions (i.e., high watercut, not enough pressure support) for abandonment, a field should be abandoned if the operating cost is higher than revenue during one time period or more.

The final output from the integrated screening model includes expected flow rates during production and net cash flows over an oilfield's lifecycle. Based on the cash flow profile, a project's Net Present Value (NPV) can be calculated based on the net cash flow as follows:

$$NPV = \sum_{t=0}^{t_{max}} \frac{NCF(t)}{(1+r)^t} \qquad \text{[Eq. 4- 26]}$$

where $r$ is the discount rate per annum. NPV discounts future cash flows and brings them to current value. A typical discount rate used in such projects is between 5 and 10 percent.

Figure 52 shows typical outputs of the screening model for a petroleum project (royalty-based economics model), and the cash flow profile is presented from the operating company perspective. Each run for this integrated screening model takes less than one second, therefore, it is computationally efficient to perform a large number of simulations under various uncertainties.

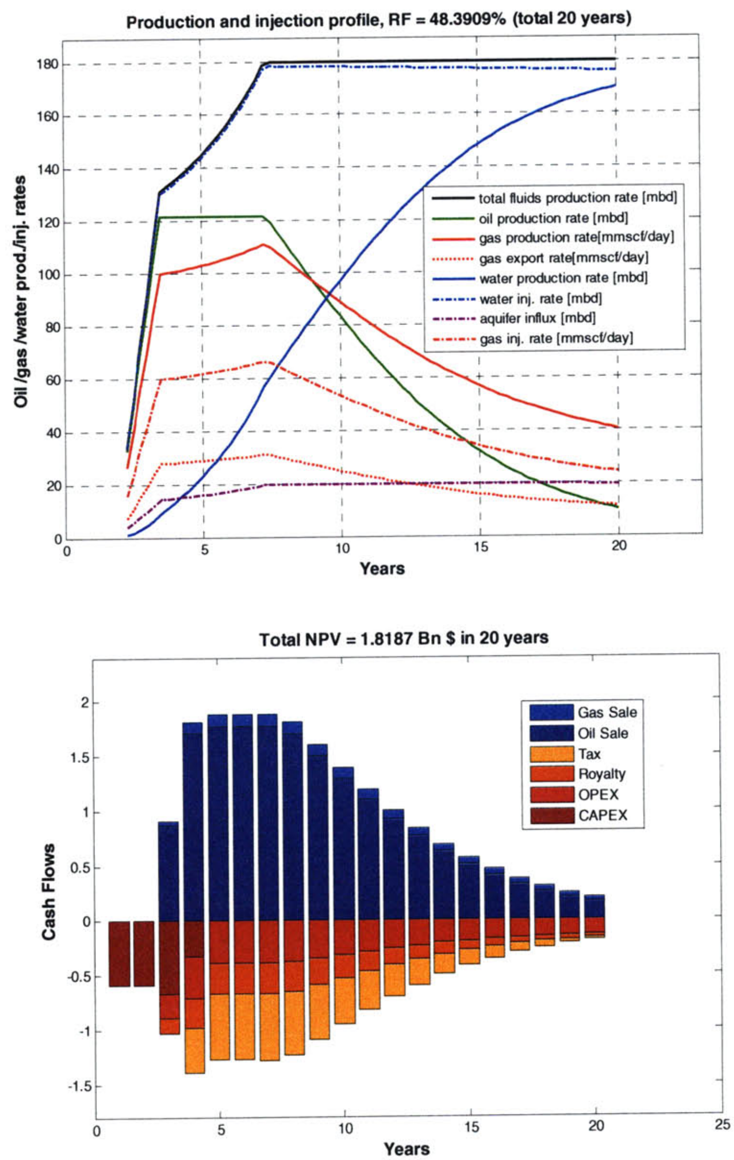


**Figure 52:** Outputs of the screening model for a typical offshore petroleum project

## 4.5 Applications of Screening Models

Screening models provide a simulation environment to explore different designs and configurations while multi-domain uncertainties are present. Screening models can be seen as a virtual computational laboratory to experiment with various field development strategies to gain insights for assisting decision making. Such investigations generally need to consider many thousands of possibilities. Compared to the standard engineering practice – using high-fidelity models for detailed technical designs -- screening models capture essential technical and economic aspects at the mid-fidelity level. Therefore, screening models can be run much faster (i.e., on the order of a 1000 times faster) than detailed high-fidelity models. Furthermore, because a screening model integrates multiple disciplines in a unified modeling and simulation environment, it avoids the manual setup time and data transfer and process time among multiple discipline tools. For the disconnected high-fidelity modeling approach, it may take up to 2/3 of an engineer's time to transfer and process data among different discipline-based tools. Thus, the screening model approach can significantly reduce the cycle time for generating design alternatives during a project's conceptual design phases. Screening models are used to quickly explore large design spaces and to identify promising design alternatives. This thesis develops a screening model for petroleum projects and explores different field development strategies (with or without multi-level flexibility) under multi-domain uncertainty.

Figure 54 illustrates a typical step-wise analysis based on the screening model for petroleum projects. There are essentially four steps in the problem.

<u>Step (0)</u>: This step is not shown in Figure 54, and it is a front-end interface between an architecture generator (e.g., Object Process Network (OPN), or Architecture Decision Graph (ADG); Simmons, 2008) and the screening model. In this step, potential field configurations and strategies at the initial stage are enumerated, either manually or with an automatic algorithm (e.g., OPN, ADG). This thesis assumes that some initial configurations are given, and concentrates on screening out the flexible strategies which can effectively evolve the initial architectures as uncertainty evolves.

<u>Step (1)</u> represents traditional practice. It applies the screening model to a conventional design that optimizes project value based on a deterministic "best guess" estimation of reservoir volumes and fixed oil and gas prices. It estimates a single number for Net Present Value (NPV).

<u>Step (2)</u> evaluates the conventional design recognizing reservoir, market, and potentially facility uncertainty. It simulates the joint distribution of these factors and calculates the NPV associated with each sample and then the average or expected net present value, (EPNV). Note carefully that the ENPV in general differs from the deterministic NPV. This is due to Jensen's Inequality

(Rudin, 1987), which is simply that the value calculated from an expected value of a parameter only exceptionally gives the true value given by the expectation over the possible states:

$$\text{ENPV} = \text{EV}[f(x)] \neq f[\text{EV}(x)] \quad \text{unless all functions are linear}$$

For example, a function $f$ is assumed to be convex on an interval $I$ if for any two points $(x_1, f(x_1))$ and $(x_2, f(x_2))$ within the interval $I$, the segment joining these two points is above the graph of the function over $(x_1, x_2)$. That is, $f((1-t)x_1 + tx_2) < (1-t)f(x_1) + tf(x_2)$ for every t in (0, 1). If $f$ is continuous on $I$, then it is equivalent to have $f\left(\frac{x_1 + x_2}{2}\right) < \frac{f(x_1) + f(x_2)}{2}$.

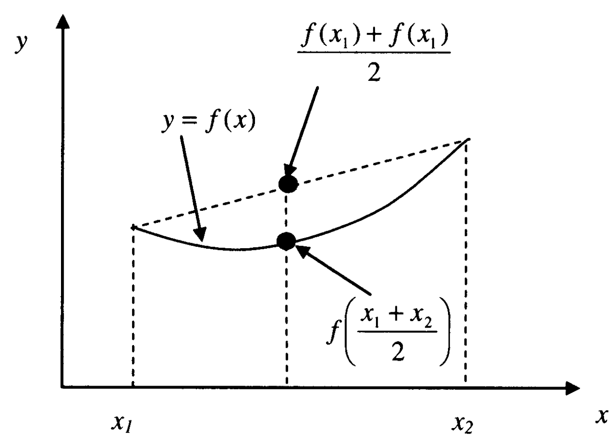


**Figure 53:** An example for illustrating Jensen's Inequality

Step (2) presents results both in a table and using the Value-at-Risk-and-Gain (VARG) curve, which gives a more comprehensive evaluation of the project under uncertain factors. This step makes two points:

- Ignoring the distribution of uncertain variables leads to an incorrect assessment of the NPV; and
- A project leads to a distribution of possible outcomes.

Steps (3) and (4) represent the screening model in action. They consider different kinds of flexibility in field development. In step (4), tie-back flexibility (adding new reservoirs) is also considered. Each possibility leads to a set of metrics as in Step (2) that can be used to rank the possible developments, most importantly in comparison with the conventional design as evaluated in Step (2). The end result of this process is a short list of the best candidates for detailed design. The process thus identifies the kinds of flexibility – the real options – that seem to improve the overall performance of the design most significantly. This is the objective of the screening process." This does not guarantee that a globally optimal solution will be found but represents a significant advance over current practice.

The next chapter will discuss different types of flexibilities in the lifecycle of a capital-intensive project.

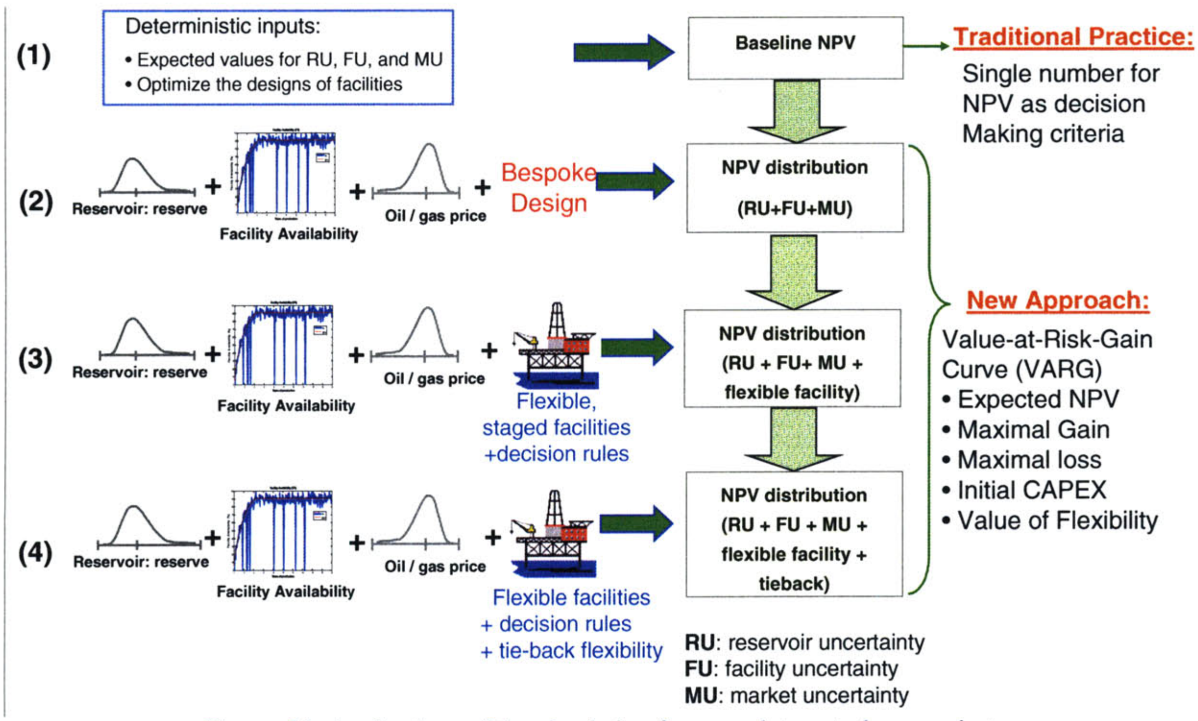

**Figure 54:** Applications of the simulation framework to petroleum projects

# Chapter 5: Flexibility in the Lifecycle of Capital-intensive Projects

## 5.1 Introduction

Capital-intensive projects, such as public and industrial infrastructure systems, involve significant amounts of capital investment while the future is uncertain. The engineering systems being designed and developed in capital-intensive projects, such as offshore oil platforms, highways, railroads, large manufacturing and production plants, and communication networks, will remain in operation over several decades once systems are fielded. During the long lifecycle, technical, economic, and social-political conditions may be significantly different from the initial conditions at the planning, design, and development stages. Thus, systems may become obsolete immediately after deployment due to fast technology advancement, or the system architectures being too rigid to be easily modified, may have to be reconfigured (Siddiqi and de Weck, 2008), and expanded for satisfying future needs.

Standard engineering practice favors detailed engineering design and analysis given a fixed set of specifications and market conditions. It can easily take engineering teams months or even years of effort to design a detailed "point-optimal" solution. Such point-optimal solutions are usually too rigid to adapt to future uncertainties. Thus, a significant amount of opportunities for mitigating risk and creating value are left unexploited.

Therefore, this chapter advocates a lifecycle perspective on development planning of capital intensive projects, and proposes design flexibility as a way to address system design under uncertainty. This approach identifies preferred solutions which can be further optimized. Three levels of flexibility are identified and modeled. This lifecycle flexibility framework is illustrated in the context of offshore petroleum projects but is applicable more broadly.

## 5.2 Lifecycle of Capital-intensive Projects

Generally, the lifecycle of capital-intensive projects includes the following distinctive phases: project planning, design, development, operation, and abandonment. The total length of these stages can span over several decades or a century (e.g., 15~30 years for offshore petroleum projects, the Whiting refinery is over 100 years old). Different stages have a distinct design space. In general, the success of projects largely depends on the decisions made in early stages of a project. Figure 55 illustrates how value creation and investment change from a project's planning phases to its execution phases. The degrees of freedom for design decrease significantly from planning phases to execution phases, so the planning phase has a larger influence on value creation. Flexibility essentially enables the design to retain degrees of freedom as much as possible during project execution and operations phases; thus, decision makers still have the freedom to shape a project's value creation profile when uncertainty unfolds in the future. Although the investment in planning is often a minor fraction of total investment, the planning phases are very critical for the success of a capital-intensive project.

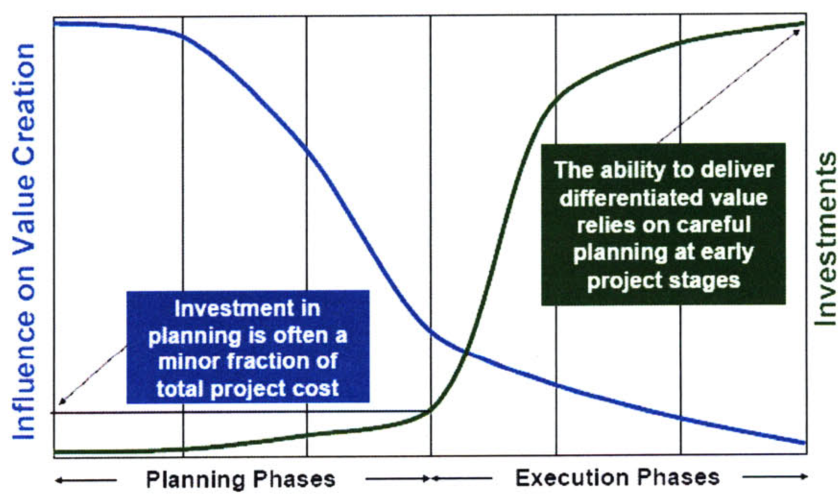


**Figure 55:** Influence in value Creation and Investment during Project Planning and Execution Phases (Figure is adapted from Saputelli *et al.*, 2008)

Figure 56 gives an overview of lifecycle processes for capital-intensive projects. Important decisions in each stage are highlighted. These decisions are also closely related to the three levels of flexibility, which will be explained in detail in the next section. Development planning of capital-intensive projects needs to take a lifecycle view. A "myopic" and "rigid" design may reduce or even destroy the potential lifecycle value of a project. For example, the Valhall oil field in the Norwegian sector of the North Sea was discovered in 1975 and production began in 1982. Over the past 25 years, the reserve estimate has grown 400%; as a result, the initial production facility (with 168 [mbd] oil production capacity) has severely constrained the potential production. Due to subsidence of the field center and reserve growth, a new Production & Hotel (PH) facility will be installed in 2009, and the new field center will extend the life of the field until 2050. However, such a reactive approach is not optimal, and the project could have potentially brought in more value earlier if the initial design had been flexible enough to accommodate the reserve growth pro-actively.

The following paragraphs discuss various decisions and flexibilities at each stage for the lifecycle of a capital-intensive project.

<u>Planning stage</u>: The planning stage involves many important processes and decisions. First of all, business opportunities need to be identified and properly verified. Then, decision makers and system architects need to conduct technical and economic feasibility studies while uncertainty is evolving. For example, in the planning stage of a petroleum project, well drilling during exploration and appraisal stages will update the previous knowledge about reservoirs, and system architects need to take into account such changes during the planning stage. In these processes, it is critical to identify sources of uncertainty and to assess their impact on choice of designs. Decision makers also need to get alignment with multiple stakeholders and secure capital investment and partnership. Finally, some economic metrics (e.g., NPV, ROI) are used to judge whether the project is economically viable.

<u>Design and development stage</u>: The design stage usually includes two sequential phases: conceptual design and detailed design:

- <u>Conceptual design</u>: during this phase, a range of project options and development concepts is explored. Each design alternative is evaluated by technical and economic metrics. In the oil and gas industry, this phase corresponds to the appraise and select stages. During these stages, appraisal wells are drilled to acquire more information about the subsurface, and then subsurface uncertainty is quantified and different facility concepts (e.g., topsides, drilling options, and subsea architectures) are explored. However, it is not yet a common practice in the oil and gas industry to set up an integrated multidisciplinary team and use conceptual screening tools. The traditional discipline-centric high-fidelity modeling processes may take up to several months and even years to generate several "promising" development options. The approach proposed in this thesis is to explore many development options more effectively using the integrated mid-fidelity model, and thus reduce the cycle time for concept screening under uncertainty.

- Detailed design: during this phase, usually one design identified by the conceptual design phase is selected for the detailed engineering design, cost estimates, and economic evaluation. Usually, high-fidelity models in each discipline are used to design and optimize the performance, schedule, and cost of the systems. In the oil and gas industry, this detailed design corresponds to a project's select to define stages. This stage may easily take up several months or a year or more.

Execution stage: In the execution stage, a design is executed under schedule, budget, and contractual constraints. For a petroleum project, the execution stage includes contracting, drilling and construction services, raw material procurement, transporting and assembling facilities on site. Depending on a project's scope and complexity and supply and demand of services, the execution stage usually takes 1~3 years.

Operations stage: In this stage, systems are deployed and operated. Commissioning of a facility is an important step. The main decisions are at the operational level, such as optimizing system throughput to maximize profit. Much effort is spent to ensure systems achieve the designed utilization and reliability. Usually the operations stage takes up the longest time period within a project's lifecycle. As uncertainties are evolving during this period, different flexibilities will be exercised if it is favorable to do so.

Abandonment stage: systems will be abandoned due to a number of reasons, such as technical reasons (i.e., obsolete technology, reaching systems' design life) or economic reasons (i.e., low demand, high operating cost). Decisions include timing of abandonment, whether or not to extend system life, re-use parts of the system, or lease or sell the system to a third party (i.e., low cost operating company).

The planning stage is the focus of this thesis. During a project's planning stage, important decisions have to be made under uncertainty. For example, choices of architectures and configurations have to be made with limited knowledge of technical performance and future market conditions. More challenging, some key inputs used for design, such as quantity of resources, are in fact unknown. Standard engineering practice is focused on detailed engineering design with given specifications. But we argue that this practice is insufficient for planning capital-intensive systems, which have a significant amount of uncertainty over the systems' long lifecycle. Chapters 3 and 4 developed uncertainty models and screening models as front-end tools to explore different designs and development strategies. This chapter aims at identifying different flexible strategies in a capital-intensive project.

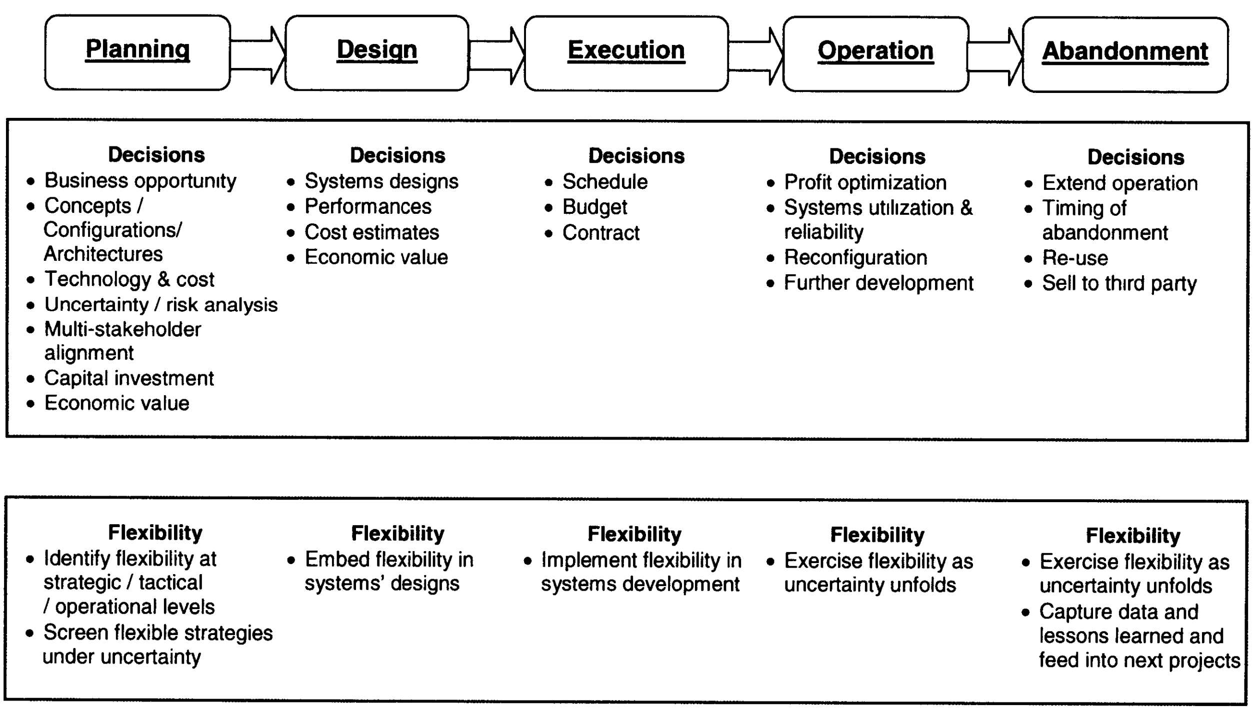


**Figure 56:** Lifecycle processes for a capital-intensive project

## 5.3 Flexibility in Capital-intensive Projects

Flexibility in design aims to improve the overall value of capital-intensive projects. Flexibility in design enables decision makers to mitigate downside risk and take advantage of new upside opportunities. As a result, flexibility can significantly improve the expected value for a project, as much as 82% (as shown in the flexible tieback case study in Chapter 7), compared to standard designs that do not incorporate flexibility. Without flexibility in design, it is usually too costly to modify systems to adapt for future uncertainties after systems are developed and deployed; sometimes it is even impossible to change system architectures due to lock-in effects (Silver, 2005) caused by the initial rigid and point-optimal design (e.g., accommodation of enhanced oil recovery, equipment on spare and weight constrained by offshore facilities). Thus, flexibility in design should be a key consideration during a project's planning stage when uncertainty is high. Flexibility may also (but not always) increase cost and complexity of an equivalent initial development, and the investment in flexibility needs to be justified.

Given the complexity and long lifecycle of capital-intensive projects, it is not easy to identify where to locate flexibility in the systems. Especially in a system's planning stage, the search space for sources of flexibility is very large given multi-domain uncertainty. Different types of uncertainty may require different flexible approaches. A system could be very flexible in some respects, but rigid in other aspects. Coupling of technical and economic systems with feedback loops makes the search for flexibilities even more challenging. Therefore, it is imperative to have a system approach to guide the search for flexibility in a project's early stage. The uncertainty simulation models and screening models provide a computational laboratory to explore different types of flexibility efficiently. In this chapter, we propose a classification of flexibility in capital-intensive projects, which serves as guidance for the search of flexibilities by using screening and uncertainty models.

In general, there are three levels of flexibility in capital-intensive systems: strategic, tactical, and operational. This classification is based on the degree of influence on the project and the time constraints involved.

### 5.3.1 Flexibility at the Strategic Level

Strategic level flexibility refers to the flexibility in systems' technology concepts and high level configurations. It is the "fundamental" flexibility, which can significantly change the way to design, develop, and operate the systems. For example, flexibility at the strategic level may include:

- Technology concept flexibility: Technology concept flexibility refers to the flexibility in choosing technology and development concepts. Ideally, decision makers and system architects need to explore different technologies and development concepts early in a project's planning stage. For example, there are multiple choices of platform concepts for deep water oilfields, such as FPSO, Tension Leg Platform (TLP), Semi-submersible, etc. Technology concept flexibility suggests considering multiple technology concepts, comparing their pros and cons, and retaining the flexibility to switch among these concepts during a project's planning phases. In the past, some capital-intensive projects (e.g., communication satellite systems such as Iridium and Globalstar) have commited too early to a fixed technology concept before fully exploring other alternatives.
- Architectural (or configurational) flexibility: Architectural flexibility refers to the flexibility to modify system architectures or configurations over time. In a generic representation, systems' configurations or architectures can be represented as networks with nodes and connections. There are two main types of configurational flexibility:
    - Add or delete nodes or connections: For development of a hydrocarbon basin, nodes may represent facilities, reservoirs, and wells. And connections may represent production, injection, service, or export flowlines as shown in Figure 57. This type of flexibility means the ability to add or abandon facilities, wells, and flowlines, or to tie in new fields in the future. As we will illustrate in Chapter 6, flexible staged development of a large oilfield can be classified as an example of this type configurational flexibility.
    - Modify or switch connections among nodes: For offshore petroleum projects, switching can mean the flexibility to modify the field-facility connections, such as tieback of a field to a facility using subsea development. As we will illustrate in Chapter 7, flexible tieback for multiple small oilfields can be seen as an example of configurational flexibility.

Figure 38Figure 57 shows the evolution of architectures for a hydrocarbon basin using a network representation, where facilities and fields are represented as nodes (shown as circle or triangle in Figure 57). There are different types of connections (e.g., production, injection, and service flowlines) between facilities and fields. In this example, initially only one central processing facility is developed during stage 1 for three fields, where gas is re-injected to a nearby field. During stage 2, a second facility is developed and connected to the three remaining reservoirs. The network representation is particularly useful to illustrate the evolution of architectures. An automatic generation of architectural paths over time is left for future work.

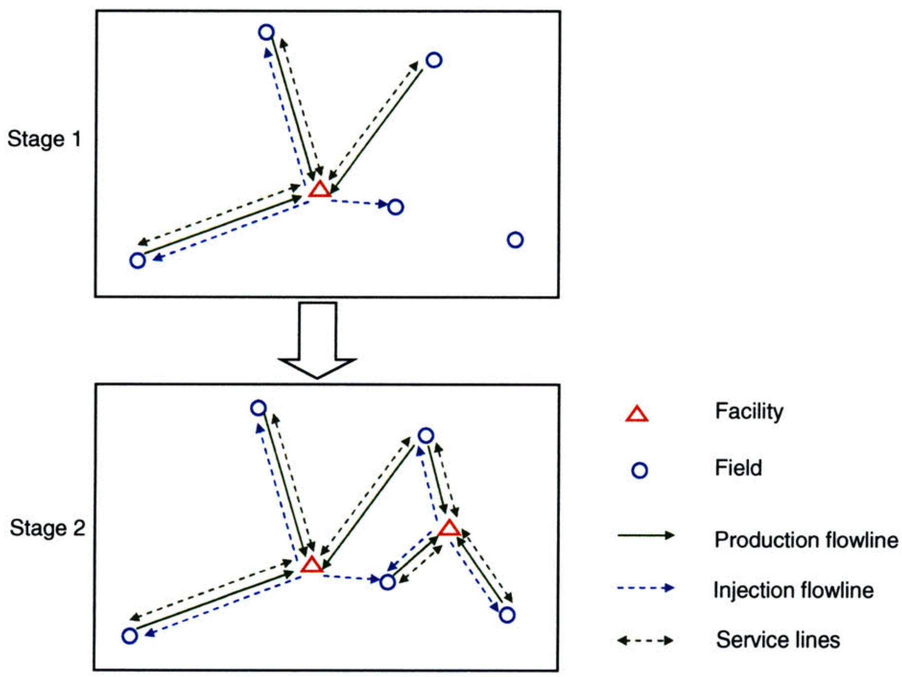


**Figure 57:** Network representation of the evolution of architectures for a hydrocarbon basin (1) Configuration at stage 1; (2) Configuration at stage 2

## 5.3.2 Flexibility at the Tactical Level

Given a system architecture or configuration, there can be flexibility to modify the systems' behavior and performance. We classified this type of flexibility as tactical level flexibility. Using the network representation shown in Figure 57, tactical flexibility means the flexibility to modify the behavior and performance of individual nodes or connections. Compared to configurational flexibility, tactical flexibility does not change the system's overall configuration or architecture (i.e. the network topology remains the same). In general, tactical flexibility may include the following dimensions:

- Facility flexibility: Facility flexibility means that the design of a single facility is flexible such that it can be easily modified to produce different products as inputs or the environment change. The relatively easy modification of a facility is enabled by design. A flexible manufacturing system is an example of tactical flexibility. A flexible manufacturing system allows re-configuring facilities (e.g., manufacturing or assembly processes or sequence, tooling) to produce different products under changing demands. For petroleum projects, facility flexibility may refer to the flexibility to accommodate multiple fluids streams with different characteristics, to operate a facility at different conditions (e.g., throughputs), and to have multiple choices to deal with flow streams (e.g., gas can be exported, re-injected, or flared).
- Capacity flexibility: Capacity flexibility refers to the flexibility to expand or contract facility production capacity. If capacity flexibility is not initially planned or designed into systems, it may be prohibitively costly to expand capacity afterwards. For offshore platforms, sometime it is even impossible to increase capacity due to limited space or insufficient sub-structural support or buoyancy for additional processing capacity through debottlenecking the process system. For manufacturing systems, such as automotive assembly plants, capacity flexibility gives firms a competitive advantage to quickly increase production with less cost to take advantage of market opportunities, or to decrease production and allocate capacity and resources toward more profitable products. This type of flexibility is also important in oil refineries.

### 5.3.3 Flexibility at the Operational Level

Operational flexibility is the flexibility to modify ways to operate a system without changing the systems' configuration or design. Operational flexibility allows systems to be operated at states which are optimal for their current conditions. Given the long period of the operations stage, operational flexibility can create a lot of value to systems' owners. Operational flexibility is largely achieved by initial designs. For example, for petroleum field operations, intelligent wells enable to monitor well productivity in real-time and to dynamically adjust lift rates to increase well productivity, and operator can turn down high water cut wells. In flexible manufacturing systems, flexible platform architectures allow to produce multiple product variants on the same assembly line. Thus, operational flexibility is enabled by strategic and tactical flexibility. Although some fixed designs permit some degree of freedom in operation, the amount of operational flexibility is typically much less than that of flexible designs.

In the network representation shown in Figure 57, operational flexibility does not change the configuration of the network, however, operational flexibility may change the quantity or direction of flows within the connections (such as switching between production or injection, changing flow rates for petroleum systems), or changing the properties of the nodes (such as the composition of fluids, allocation of capacity to multiple fields).

The idea of classifying flexibility into different levels corresponds to the similar ideas of providing taxonomy to organize a concept in the literature. For example, Henderson-Clark's taxonomy of innovation classifies innovation into the four categories (i.e., radical, architectural, modular, and incremental innovation) according to the level of impact on component and architecture knowledge. Tong and Sriram (1992) proposed a taxonomy for engineering design, which classifies design into the three categories (i.e., routine design, innovation design, and creative design) according the level of knowledge of the relations between systems' architectures and functions.

Table 13 summarizes the three levels of flexibility in capital-intensive projects. It compares the three levels of flexibility in terms of definitions and network representation. Examples are given in petroleum projects and the automotive industry.

**Table 13:** Three levels of flexibility

| | Definitions | In network representation | Examples |
|---|---|---|---|
| Strategic Flexibility | Flexibility to evolve a system's architecture, (or configuration) over the lifecycle of a project | Change the number and connectivity for nodes and connections | • Staged development or tieback flexibility for a hydrocarbon basin<br>• Flexible strategies for global manufacturing plants for an automotive company |
| Tactical Flexibility | Flexibility to change the design, behavior, or performance of subsystems after the system has been fielded | Change the properties of existing nodes or connections | • Capacity expansion flexibility of an oil platform<br>• Flexible assembly lines (for multiple models) for an automotive plant |
| Operational Flexibility | Flexibility to change the operations of the system without modifying a system's architectures or designs | Change the flows (e.g., rates, directions, types) in a network | • Active reservoir management for improving hydrocarbon recovery<br>• Flexible shifts or throughputs of an automotive plant |

## *5.4 Flexibilities in Offshore Petroleum Projects*

Offshore petroleum projects are complex and capital-intensive. These projects easily cost hundreds of million to tens of billions of dollars of investment. The lifecycle of these projects, from exploration to abandonment, usually takes 20~50 years. During a project's early stage, a significant amount of uncertainty exists in reservoir, development cost and schedule, and the market environment. However, important decisions, such as field development architecture, choices of technology, facility capacity, and future tieback options need to be made in projects' early stage while uncertainties are evolving. If an offshore oilfield's development architecture and design are too rigid, it will be very costly, if it is not impossible, to change system design or operations during the operational phase. Therefore, it is very critical to explore flexibilities during a project's planning stages. Given the complexity and uncertainty in petroleum projects, it is not straight forward to identify various sources of flexibility. So, this section focuses on identifying and evaluating flexibilities in the lifecycle processes of petroleum projects.

Before discussing the flexibility in petroleum projects, let us understand the "problem landscape" for development of a hydrocarbon basin. Different development strategies have their unique flexible options in field configurations and system designs. Figure 58 shows the problem landscape. The horizontal axis represents the numbers of reservoirs (or fields) in a basin, and the vertical axis represents the numbers of facilities (or platforms). Depending on the number of reservoirs and facilities, there are four types of field architectures.

- Single reservoir and single facility (Quadrant A): This is the simplest scenario. The development strategy is to build a single production and injection platform (fixed or floating depending on water depth) for the oilfield at moderate size. The coupled reservoir and facility model developed in Chapter 4 applies to this case, which can be used a building block for more complex field development scenarios.
- Multiple reservoirs and single facility (Quadrant B): In this scenario, there are multiple small reservoirs (or fields) in a basin. The quantity of hydrocarbons in each field alone may not be large enough to economically justify a dedicated facility. Therefore, the development concept is to tieback multiple fields to a central production facility. The main decisions are location of the facility, field configuration, number of tieback fields, and timing of tieback, etc. Chapter 7 will present a detailed tieback case study to compare different development strategies for this scenario.
- Single reservoir and multiple facilities (Quadrant C): Given a giant monolithic oilfield, the development strategy could be to build multiple facilities to produce the hydrocarbons. Usually, these facilities are similar (same concepts) but phased over time. So the main decisions include how to standardize facilities or processes to reduce cost, and how to phase development over time in order to gain learning benefits or to reduce reservoir uncertainty. Chapter 6 will illustrate different development strategies for this scenario.
- Multiple reservoirs and multiple facilities (Quadrant D): This can be treated as a hybrid case based on the previous three scenarios. In this scenario, there are more choices to connect reservoirs with facilities (choice of mapping, one to one, one to many, many to one). Future complex developments may increasingly fall into this category.

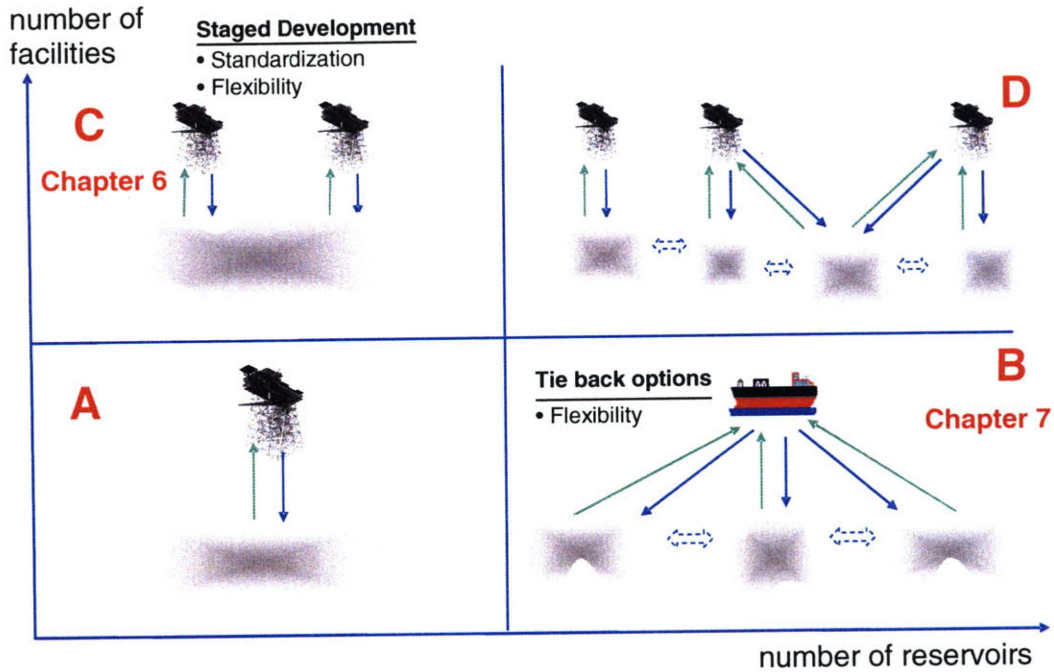


**Figure 58:** Problem landscape for the development of a hydrocarbon basin

Table 14 gives examples for the four types of development scenarios shown in the problem landscape.

**Table 14:** Examples for the four types of development scenarios

| Types of development strategy | Examples |
|---|---|
| A: Single reservoir and single facility | Alaska Prudhoe Bay oil field, Gulf of Mexico Thunder Horse field |
| B: Multiple reservoirs and single facility | Angola B18 Greater Plutonio project, Angola B31 Plutao, Saturno, Venus, Marte (PSVM) project |
| C: Single reservoir and multiple facilities | Azerbaijan Azeri-Chirag-Gunashli (ACG) oil field project |
| D: Multiple reservoirs and multiple facilities | Development of a hydrocarbon basin with multiple fields through phased development of multiple platforms |

In this thesis, we propose two ways to represent the topological configuration for a hydrocarbon basin with multiple reservoirs and multiple facilities:

- Network Representation: In this representation, reservoirs and facilities are represented as different nodes; the flowlines (e.g., production, injection, services, and export flowlines) between reservoirs and facilities are shown as links between nodes. This type of network corresponds to a bi-partite graph, where two sets of nodes are present (i.e., reservoir, facility). However, there are possibilities that reservoirs can be directly connected to other reservoirs, or facilities can be directly connected to other facilities. An example of using networks to represent the architecture of a hydrocarbon basin is shown in Figure 57.
- Matrix Representation: A network can also be represented as a connectivity matrix (adjacency matrix). For a hydrocarbon basin with $n$ number of reservoirs and $m$ number of facilities, an $(n+m)$ by $(n+m)$ square matrix can be used to represent the connectivity space between reservoirs and facilities, where "1" represents a potential connection and "0" represents the absence of a connection. Figure 59 shows a generic $n+m$ matrix for representing the connectivity between reservoirs and facilities in a hydrocarbon basin. This matrix is symmetric and it only shows the connectivity between reservoirs and facilities, but the directions of the connection are not differentiated. The instances of the matrix can be automatically generated by algorithms. For example, Keller (2008) applied OPN to generate feasible oilfield architectures (e.g., the connectivity between reservoirs and facilities) for given constraints (e.g., maximum number of connections for a facility or reservoir, distance constraints for connecting a reservoir to a facility). This thesis assumes initial configurations (or $n+m$ matries) are given, and then simulates how the initial configuration evolves over time under uncertainty. Chapter 6 and 7 will illustrate the evolution from an initial architecture for the scenarios B and C in the problem landscape, respectively.

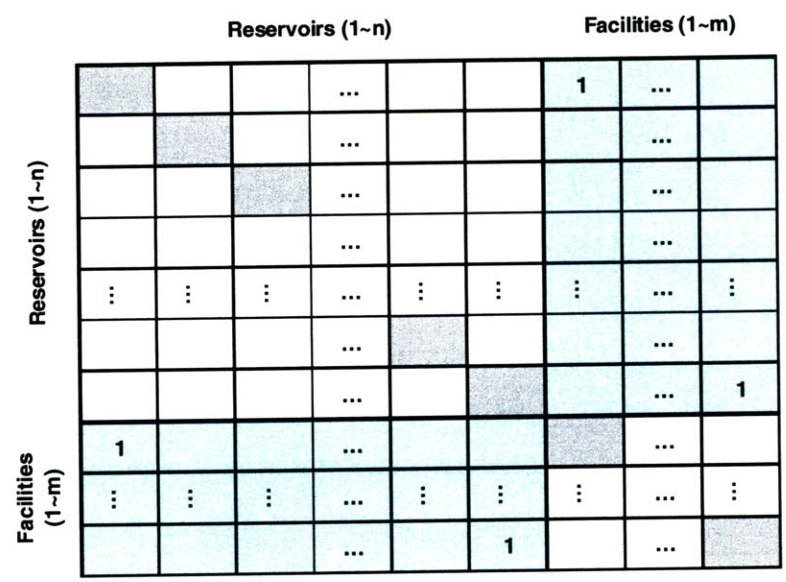


**Figure 59:** An $n$+$m$ matix for representing the connectivity space between reservoirs and facilities

### 5.4.1 Inter-facility Flexibility

Flexibility at the inter-facility level is strategic level flexibility which looks at flexibility for the whole field development. Typical examples are flexible staged development for a single large oil field or tie-back of a new reservoir to an existing platform. At this level of flexibility, entire platforms can be added, moved or retired from the field, or new reservoirs can be tied back to existing facilities over time. Flexibility at the inter-facility level is configurational flexibility, and it defines the topology relationships between reservoirs and platforms. In terms of network representation, inter-facility flexibility involves more than one node or edge in a network. Possible actions include adding, modifying, or deleting nodes or edges in a network.

### 5.4.2 Intra-facility Flexibility

Intra-facility flexibility represents the flexibility at the tactical level, which applies within one facility. Examples of such flexibility include adding extra space in the production, drilling or cellar deck allowing later addition of modules such as compression or the addition of more water injection pumps, flexibility to drill and accommodate more production or injection wells from a platform. Flexibility at the intra-facility level defines the design options of an individual facility (e.g., production, injection, or well platform). In terms of network representation, intra-facility flexibility involves modifying the properties of a single node or edge.

### 5.4.3 Operational Flexibility

Operational level flexibility does not change the configurations or designs of the systems. For example, to achieve higher oil recovery rates from a reservoir, field operators can actively manage production by increasing water and gas injection rates, or changing the mix of incoming fluids from different wells to maximize oil production and revenues. The field architectures and the designs of facilities will not be affected by exercising operational flexibility. In terms of network representation, operational flexibility changes the flow rates in the connections without modifying network configurations.

## *5.5 Summary*

Identifying the most desirable sources of flexibility in complex and capital-intensive projects is not a straightforward task. The standard literature on real options assumes that the sources of flexibility (the options) are either known or obvious. However, this is not true for complex engineered projects, such as offshore oil and gas systems. In this chapter, we identify three levels of flexibility in offshore petroleum projects. The main question is: how to screen and pre-evaluate these flexibilities under both technical and economic uncertainty. This thesis develops an integrated screening approach. With the integrated screening model, system architects can quickly explore the design space, experiment with decision rules for exercising flexibility, simulate and compare flexible development strategies under multi-domain uncertainty, and select the most promising flexible strategies based on the distribution of outcomes, such as Value-at-Risk-Gain (VARG) curves.

This chapter presents a qualitative discussion on the different levels of flexibility for petroleum projects. The cost models for flexibility are proposed in Section 4.4.2 of Chapter 4. However, the specific assumptions for the cost of options and flexible strategies are illustrated in the case studies in Chapters 6 and 7.

Chapter 6 and 7 will demonstrate this approach through two case studies. The first case study corresponds to the Quadrant C of the problem landscape as shown in Figure 58. This case study compares four different development strategies (*i.e.*, one big stage, pre-determined three staged, flexible staged, and reactive staged development) for a large hypothetical oil field. The second case study corresponds to the Quadrant B in the problem landscape, and it models the three types of flexibility (i.e., tieback flexibility, platform capacity expansion flexibility, and active reservoir management flexibility) for the development of a hydrocarbon basin with multiple small oil fields. The Design of Experiments (DOE) and VARG approaches allow to quantify the value of flexibility. In both case studies, reservoir, facility, and market uncertainty are turned on sequentially. These two case studies show that flexibility can significantly improve a project's expected value, reduce downside risks, and extend upside gains.

# Chapter 6: Case Study I: Staged Development of a Large Offshore Oil Field

The problem landscape shown in Chapter 5 includes four quadrants, which represent the mapping space between reservoirs and facilities (e.g., Central Processing Platform (CPF)):

- Quadrant A: Single reservoir and single facility
- Quadrant B: Multiple reservoirs and single facility
- Quadrant C: Single reservoir and multiple facilities
- Quadrant D: Multiple reservoirs and multiple facilities

Quadrant A is the simplest scenario and has been widely studied in petroleum engineering. The remaining three quadrants are more challenging. This chapter develops a staged development strategy for a large oil field (i.e., Case Study I), representing the Quadrant C. Chapter 7 develops a tieback case study (i.e., Case study II) in quadrant B. Quadrant D is a hybrid scenario based on A, B, and C. This thesis does not develop any particular case for quadrant D, but the general approaches shown in Chapters 6 and 7 can be applicable to hybrid cases.

## *6.1 Introduction*

This case study deals with the potential development strategies of a hypothetical large oilfield. It corresponds to the scenario C in Figure 58, in which a phased development is applied for a large monolithic oilfield (based on a hypothetical oil field). In this chapter, we consider four alternative development strategies.

## *6.2 Model of Four Field Development Strategies*

In this section, we will explain how these four field development strategies are formulated and what the assumptions are.

### 6.2.1 One Big Stage ('Monolithic') Development

This represents a conventional design – a facility optimized to deal with the best estimates of the size of the field and predefined oil prices. This strategy gains benefits due to Economies of Scale (EOS). EOS favors a design with a bigger platform as per unit capacity CAPEX is less if capacity is higher. However, this design might lead to oversized capacity if the reservoir underperforms or lead to more exposure to the risk of initial capital investment if market conditions turn out to be unfavorable. Or the design could be undersized and unable to take advantage of the upside in reservoir volumes or market uncertainty, and thus looses the value it could have captured if more production than anticipated is required (see Valhall field in the North Sea).

Figure 60 shows the production, injection, and cash flow profiles for the one big stage development strategy by assuming the P50 values for reservoir, facility, and market uncertainties over the lifecycle of the oilfield.

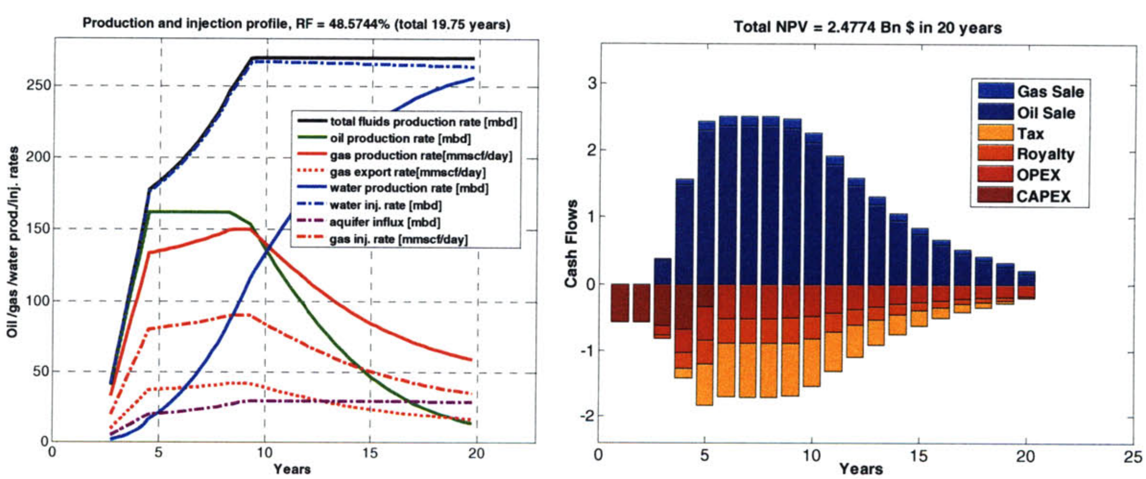


**Figure 60:** Production, injection, and cash flow profiles for one big stage development

### 6.2.2 Pre-determined Three-stage Development

This strategy develops the field through three identical stages phased in a pre-determined way. There are two main advantages of this strategy: Firstly, the subsequent stages can benefit from the learning from the previous stages due to the repetition of the design and development of the same platform. Secondly, the capital investments are phased over time and thus reduce the initial capital investment required. The downsides of this strategy include:

- Looses the economies of scale as the cost of per unit capacity is higher for small platforms than big platforms.
- Has a slow production ramp-up due to phased development and thus delays the positive cash flows in terms of revenues.
- Makes a pre-commitment to stage 2 and 3 at year 0 before reservoir and market uncertainties unfold.

The projected production, injection, and cash flow profiles for the pre-determined three-stage development are shown in Figure 61, where reservoir, facility, and market uncertainties are assumed at their P50 values.

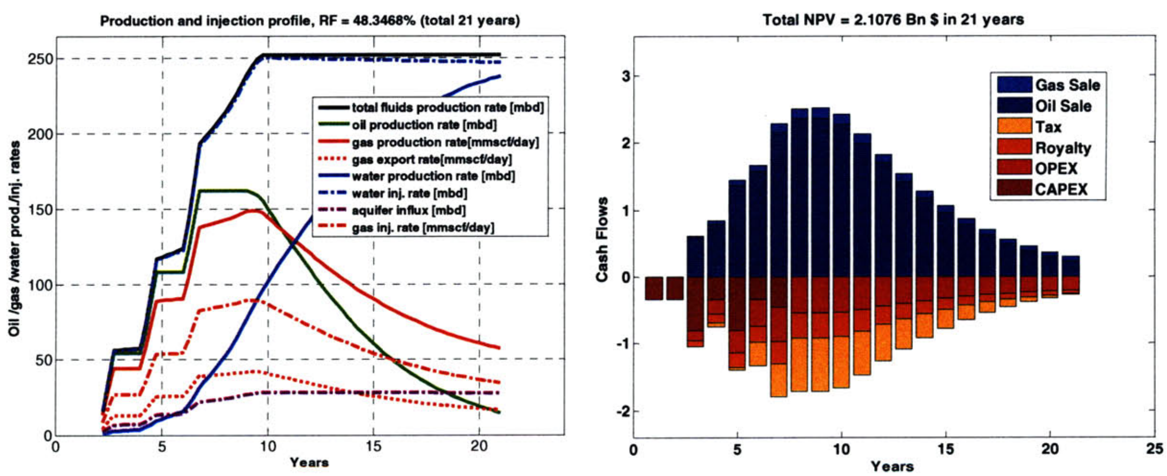


**Figure 61:** Production, injection, and cash flow profiles for pre-determined three-stage development

This strategy assumes a conservative 90% learning factor for CAPEXs in the three stages through use of standardized designs. The standard learning curve model is shown in Equation 6-1:

$$Y(x) = Y_0 x^n \qquad \text{[Eq. 6 - 1]}$$

where $x$ is the number of platforms built; $Y_0$ is the CAPEX for the first stage; $Y(x)$ is the CAPEX for stage $x$; $n = \log b / \log 2$, where $b$ is the learning factor. In this case study, we assume b = 90%.

Thus, the CAPEX of the second stage is 90% of the first stage, and the CAPEX of the third stage is 84.6% of the first stage.

### 6.2.3 Flexible Staged Development

For flexible staged development, the number of stages, size of each stage, and the timing of stages are all flexible. The decisions to add stages depends on the difference between the current estimate of remaining reserves and the amount of reserve that can be handled by existing stages within the fixed time horizon for the project. If market uncertainty is taken into account, there is a minimum crude oil price above which the decision to add stages can be exercised (if the reserve triggering conditions are satisfied). In this case study, we develop a decision rule to determine when to add additional stages with how much capacity. When a triggering condition is satisfied, the decision rule will exercise the options to add platforms with various capacities. However, it will take a certain period of time (24~32 months depending on the size of a stage) for the project to bring the new capacity online. This time between the decision to expand and when the new capacity actually comes online is very important and it represents a major difference with financial options.

There are different ways (e.g., logical statements, decision trees) to represent a decision rule. Figure 62 shows the decision rule implemented here in terms of an *iterative decision tree* for the flexible staged development case. In this example, the decision rule only takes into account reservoir uncertainty. In Section 6.4 of this chapter, we will show the simulation results by turning on reservoir, facility, and market uncertainty in a sequential way, in which the decision rule is constructed based on the evolving reserve estimate (and possible crude oil market prices). This decision rule includes the following elements:

- At time zero, an initial stage with 75% capacity is built, which is based on the median of initial reserve estimates (i.e., 600 mmbbls). It assumes that the cost of an expansion option (e.g., adding an additional stage) is 10% of the platform cost of the initial stage. This defines the cost of option $C_{\cos t\_of\_option}$, but the actual cost of exercising capacity expansion $C_{\text{expand}}(t)$ (as defined in Equation 4-14) is deferred into the future as uncertainty unfolds.

- Between year 3 and 10, at the beginning of each year, the decision rule determines whether or not to add additional stages (and if yes, how much capacity for the stage) based on $\Delta(t)$, where $\Delta(t)$ is the difference between *the current estimate of reserve* and *the amount of reserve being handled by existing facilities* in the project's remaining time horizon. The *current estimate of reserve* is obtained from the reserve evolution model (as developed in Chapter 3). The amount of reserve being handled by existing facilities is the sum of projected oil production profiles of all implemented stages given the remaining time horizon for the project. It assumes the lifecycle for the entire project is 21 years. The model contains a function[12] to transform the platform capacity to the amount of reserve that can be handled by the existing capacity over various remaining times.
- According to the value of $\Delta(t)$, the decision rule selects and adds stage(s) with different capacities. If $\Delta(t)$ is large enough, two stages can be added simultaneously. The conditions (e.g., $200 < \Delta(t) \leq 350$ ) are determined through trial and error. These conditions give reasonable responses based on a series of test runs. One of the future work directions is to fine tune these conditions and possibly optimize the decision rules using formal optimization algorithms.
- The decision rule only allows to add additional stages between year 3 and year 10. The decision does not allow to add stages over the entire lifecycle of project due to the following reasons: First, the volatility of the initial reserve estimate is very high, thus, decisions may turn out to be wrong or suboptimal due to incorrect estimates of the reserve. On the other hand, if a decision is postponed for too long (the reserve estimate may be very accurate), there is not sufficient time to recover the investment due to the fixed time horizon. The project will be penalized due to the time value of money (delayed revenue). For this specific decision rule, the time window (between year 3 and 10) for enabling flexibility is also determined based on trial and error. Later in this chapter, we will conduct a sensitivity study on the timing of when flexibility can be

[12] This function is based on the nominal oil production profile for the oil field. It varies accordingly to different production capacities and time horizons. This function is NOT simply oil production capacity * remaining time, because the oil production rate usually cannot be maintained at peak rate for the remaining time due to water break in later during production.

exercised. It appears that the expected NPV reaches an optimal value when flexibility can be exercised starting in year 3.

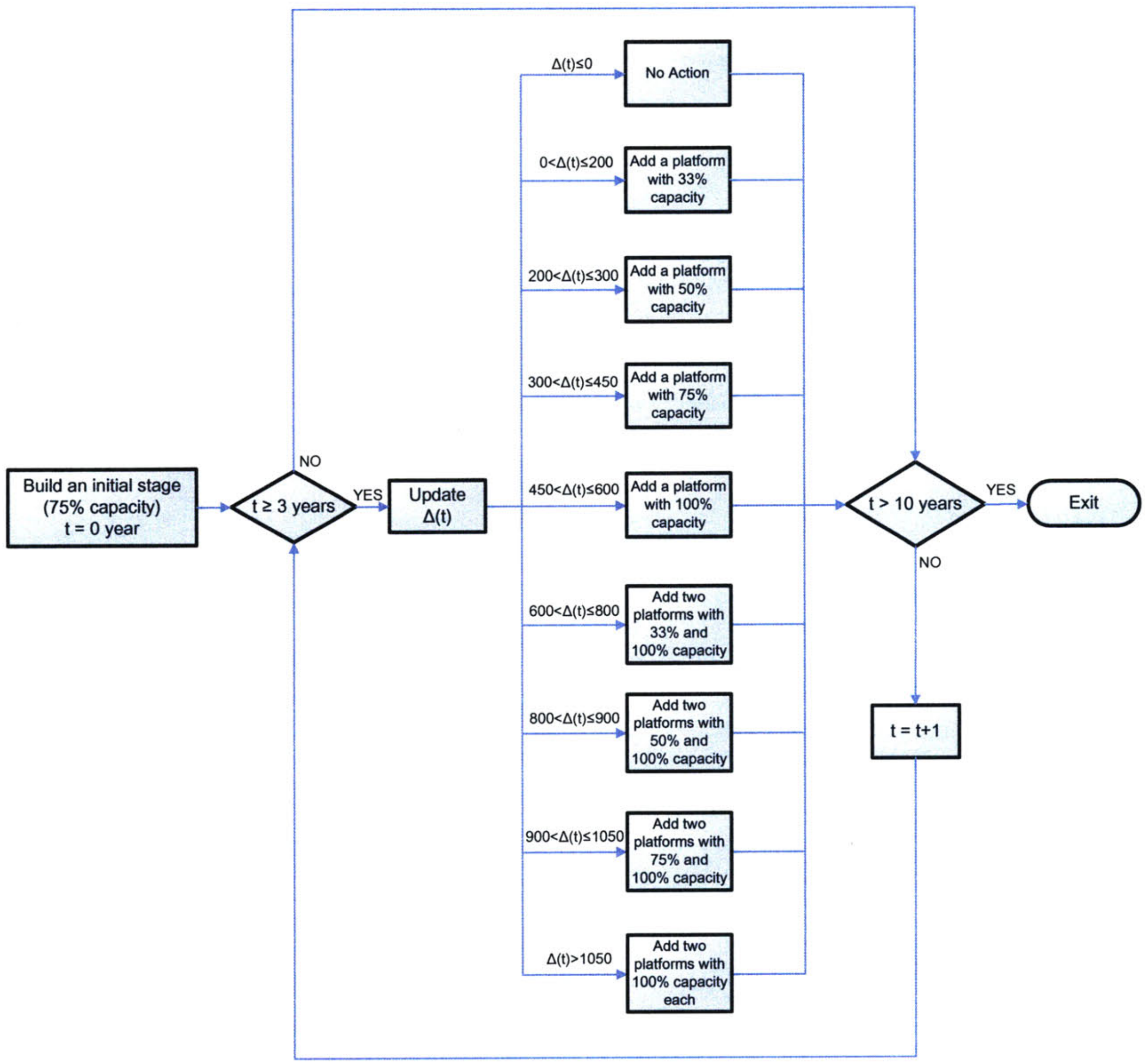


**Figure 62:** An iterative decision tree representation of the decision rule for the flexible staged strategy

Figure 62 shows a specific type of decision tree – *a time iterative decision tree*. In this decision tree, there are 9 different decision branches within each time step. During each time step, the decision of choosing a branch is made based on the value of $\Delta(t)$. Because there are 8 discrete time steps (from year 3 to 10) and there are 9 branches within each time step, this decision rule in fact defines $9^8$= 43,046,721 different evolution paths for the field architecture. The maximum number of new platforms is 16 ($2\times8=16$) if the $\Delta(t)$ turns out to be greater than 1050 in each time step from year 3 to year 10. But this extreme scenario doesn't occur given the sample for reserve estimate. For this particular reserve estimate sample, the maximal number of stage getting implemented is 5.

Another way to represent the decision rule is to use logical statement (i.e., IF…ELSE…THEN…). It can be seen as the pseudocode for implementing the decision rule.

```
At Year 0
   Build a platform with 75% capacity (for P50 of reserve estimate: 800 mmbbls)
   Design flexibility to add platforms (cost of options: 10% of the initial stage)

FOR t = 3:10  (year 3 to year 10)
   Δ (t) = reserve_estimate(t) – reserve_handled_by_existing_platform(t, capacity)

   IF 0 < Δ (t) ⩽ 200
         THEN add a platform with 33% capacity
   ELSEIF 200 < Δ (t) ⩽ 300
         THEN add a platform with 50% capacity
   ELSEIF 300 < Δ (t) ⩽ 450
         THEN add a platform with 75% capacity
   ELSEIF 450 < Δ (t) ⩽ 600
         THEN add a platform with 100% capacity
   ELSEIF 600 < Δ (t) ⩽ 800
         THEN simultaneously add two platforms with 100% and 33% capacities
   ELSEIF 800 < Δ (t) ⩽ 900
         THEN simultaneously add two platforms with 100% and 50% capacities
   ELSEIF 900 < Δ (t) ⩽ 1050
         THEN simultaneously add two platforms with 100% and 75% capacities
   ELSEIF Δ (t) ⩾ 1050
         THEN simultaneously add two platforms with 100% capacity each
   END
END
```

Table 15 shows the definitions of stages. These definitions are informed by actual examples and runs with the OGM software. In order to simplify the problem, we made the following assumptions:

- The percentage of capacity corresponds to the oil throughput of a platform. We define a platform with 180 MBD oil throughput as 100% capacity, which can cumulatively process 800 mmbbls (million barrels) of crude oil over the fixed time horizon.
- We assume that the reserve, production, and injection rates are adjusted linearly according to the platform capacity. For example, the production and injection rates of the 50% capacity stage are half of the rates for the stage with 100% capacity.

- The number of producers (oil production wells) is calculated based on the amount of reserve each producer can recover. We assume all producers are identical and can recover 30 mmbbls reserve at maximum. For example, it requires 20 producers to recovery 600 mmbbls for a stage with 100% capacity.
- We assume a 1:1 ratio between water injectors and producers, a 1:4 ratio between gas injectors and producers. The actual numbers of water and gas injectors are rounded up to their nearest integers.
- The 100% capacity platform cost is calculated by a regression model developed based on OGM. The details of the regression model are shown in Appendix 2. Other platform (i.e., 75%, 50%, and 33% capacity) costs are computed based on the Equation (4-12) $\sum_{t=0}^{t_{dev}} C_{plat}(t) = b_0^{plat} + b_1^{plat}(q_{cap\_oil})^{a^{plat}}$ where parameter $b_0^{plat}$ is assumed to be zero (Thus equation 4-12 becomes a formula representing standard economies of scale) and parameter $b_1^{plat}$ is calculated based on the 100% capacity platform. The factor $a^{plat}$ (factor for EOS) is assumed as 0.6.
- Subsea and well costs are calculated based on the total number of producers and injectors. We assume that each well (subsea, drilling, completion cost) costs 70 million dollars.
- The total CAPEX is the sum of platform cost, subsea and well cost. For the flexible staged strategy, the cost of expansion (e.g., adding a stage) is computed based on the Equation 4-15 $C_{expand}(t) = m\left(C_{plat\_\exp}(t) + C_{well\_\exp}(t) + C_{surf\_\exp}(t)\right)$, where $m$ is assumed to be 0.9. It says that the cost of expansion is 90% of its nominal CAPEX as shown in Table 15. The cost of an option to acquire this flexibility is assumed to be 10% of the platform cost of the initial stage. However, the cost of adding a stage without flexibility is equal to its nominal CAPEX, where $m$ is equal to 1. For the reactive staged strategy, it assumes that the development time of the future stage is the same as the flexible staged strategy.
- The model assumes a 95% learning factor on CAPEX reduction for the flexible staged development. Although future stages may not be identical to the initial stage, we assume that some learning occurs, but the learning effect is not as strong as the pre-determined three-stage development (with 90% learning factor for the three identical stages).

**Table 15:** Definitions of the stages

| Definition of a stage (% of capacity for single big stage) | **100%** | **75%** | **50%** | **33%** | |
|---|---|---|---|---|---|
| STOOIP | 1200 | 900 | 600 | 400 | mmbbls |
| OFGIP | 150 | 113 | 75 | 50 | bcf |
| Reserve | 600 | 450 | 300 | 200 | mmbbls |
| Total Liquids | 300 | 225 | 150 | 100 | mmstb |
| Oil Throughput | 180 | 135 | 90 | 60 | mmstb |
| Produced gas | 225 | 169 | 113 | 75 | mmscfd |
| Produced water | 300 | 225 | 150 | 100 | mmstb |
| Water injection | 330 | 248 | 165 | 110 | mmstb |
| Gas injection | 100 | 75 | 50 | 33 | mmscfd |
| Pre-drilled producers | 5 | 4 | 3 | 2 | |
| Total producers | 20 | 15 | 10 | 7 | |
| Water injecters | 20 | 15 | 10 | 7 | |
| Gas injectors | 5 | 4 | 3 | 2 | |
| Drilling rampup time | 24 | 18 | 12 | 8 | month |
| Development time | 30 | 24 | 24 | 24 | month |
| Platform cost | 0.96 | 0.81 | 0.63 | 0.50 | Bn $ |
| Total subsea and well cost | 1.8 | 1.36 | 0.92 | 0.64 | Bn $ |
| Total CAPEX | 2.76 | 2.17 | 1.55 | 1.14 | Bn $ |

Figure 63 shows the normalized costs for platform, subsea and wells, and total CAPEX under the different capacities. As the capacity increases, the platform costs do not grow as quickly as subsea and well costs, because platform cost is calculated based on the EOS formula with an exponent of 0.6, while subsea and well costs grow linearly with the number of wells. The normalized total CAPEX falls between these two.

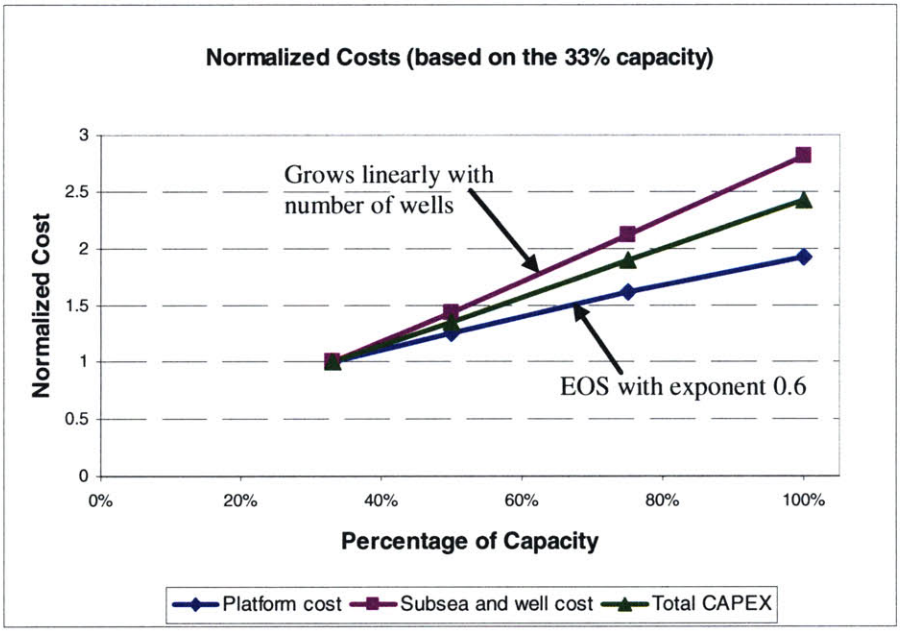


**Figure 63:** Normalized costs (based on the platform with 33% capacity)

### 6.2.4 Reactive Staged Development

The fourth strategy is reactive staged development. This strategy starts with the same configuration as the one big stage development. The reactive staged strategy does not build in any flexibility in design, thus, there is no cost of a real option for the initial stage, but it can respond to reservoir uncertainty in a reactive way. We assume that this strategy can add a second stage with 100% capacity if $\Delta(t) > 300$. Because this is a reactive way to respond to the reservoir uncertainty, it is more expensive (CAPEX expansion factor $m$ is equal to 100%) to add the second platform than flexible staged strategy where $m$ = 90%. We also assume that this reactive strategy can only add one additional stage with 100% capacity due to infrastructure constraints (e.g., capacity of export pipelines, onshore infrastructure).

## *6.3 Multi-domain Uncertainty*

Section 6.2 formulates the four alternative field development strategies. In order to assess the possible performance of these strategies, we need to simulate these four strategies under multi-domain uncertainties. This section defines the parameters for reservoir, facility, and market uncertainty models.

**Reservoir Uncertainty:**

Table 16 shows the parameters and assumed values for the reserve evolution model. Before the simulation, 400 evolutionary paths for the reserve estimate are simulated based on the reserve evolution model. Figure 64 plots these 400 evolution trajectories for the mean of reserve estimates. As shown in Figure 64, the estimates are volatile during the initial several years, and become relatively stable after 10 years except for a few disruptive changes.

**Table 16:** Parameters for the reserve evolution model

| Parameters | Values |
|---|---|
| Evolution of P50 | |
| $\mu_0$ | 800 mmbbls |
| $\Sigma_0$ | 0.6 |
| $\beta$ | 0.5 |
| Evolution of variance of P50 | |
| $\sigma_0$ | 0.3 |
| $\alpha$ | 0.2 |
| Evolution of disruptive changes | |
| $\gamma$ | 0.3 |
| $p_{r0}$ | 0.05 |
| Simulation setup | |
| $\Delta t_r$ | 1 year |
| $n_{sample}$ | 400 |

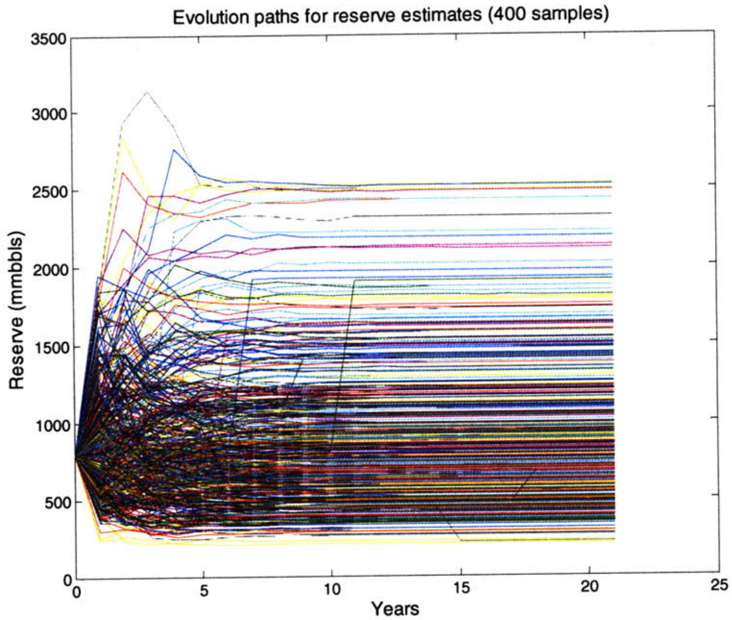


**Figure 64:** Evolutions of Reserve Estimates (400 samples)
(Initial distribution for P50, mean: 800, std: 0; the final distribution for P50, mean: 889, std: 454)

**Facility (Availability) Uncertainty:**

Table 17 shows the parameters and their assumed values for the facility uncertainty model. The facility availability model (such as Equations 3-10 and 3-11) developed in Chapter 3 is used to simulate the facility uncertainty in this case study. A sample of facility availability is shown in Figure 30, where the $t_{ramp\_up}$ is different from Table 17.

**Table 17:** Parameters for Facility (Availability) Uncertainty Model

| Parameters | Values |
|---|---|
| $a$ | 0.05 |
| $b$ | 0.90 |
| $\beta_f$ | 0.043 |
| $p_f$ | 0.05 |
| $t_{ramp\_up}$ | 8~24 months<br>depending on platform capacities |
| $\Delta t_f$ | 3 months |
| $t_{\max}$ | 21 years |

**Market Uncertainty:**

In this case study, a GMB model is applied to simulate the evolution of crude oil market prices. The parameters and their assumed values for this uncertainty model are shown in Table 18. Figure 65 shows 400 simulations for the evolutions of crude oil prices based on the GMB model.

**Table 18** Parameters for Market Uncertainty Model

| Parameters | Values |
|---|---|
| $P_0$ | \$40 per barrel |
| $\mu_m$ | 2% per year |
| $\sigma_m$ | 10% |
| $\Delta t_m$ | 1 years |
| $t_{\max}$ | 21 years |

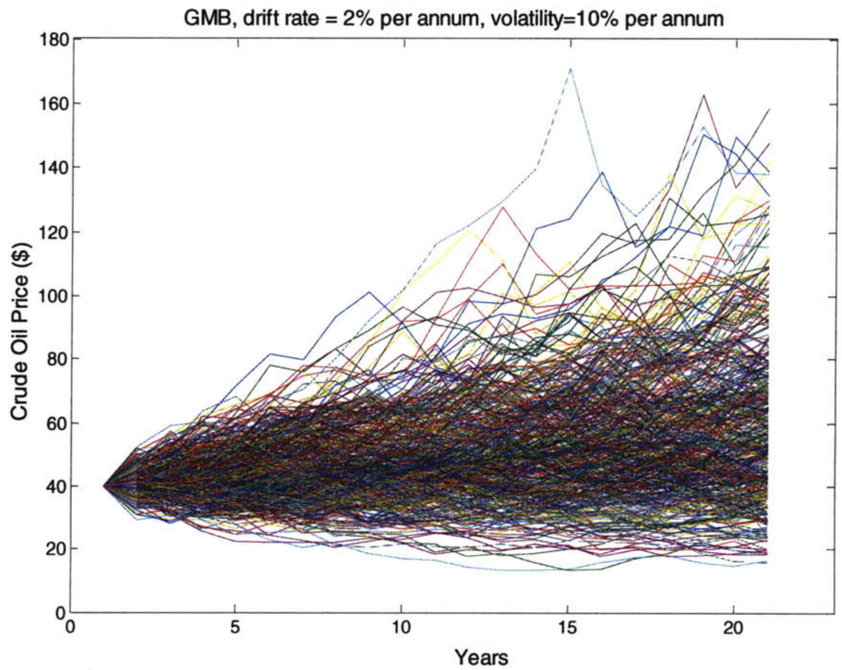


**Figure 65:** Evolutions of crude oil prices based on the GMB model (400 trajectories)
(Initial distribution for $P$, mean: \$40, std: 0; the final distribution for $P$, mean: \$61, std: \$26)

## *6.4 Simulation Results and Discussions*

This case study simulates four types of strategies under reservoir, facility, and market uncertainty. We sequentially turn on these uncertainties to examine their effects on the VARG curves.

### 6.4.1 Simulations with RU

For the first step, we only turn on reservoir uncertainty while assuming that facility availability and market prices are at their mean values. Figure 66 shows the VARG curves for the four strategies and Table 19 summarizes the key statistics of the economics metrics (i.e., NPV, CAPEX) for each strategy.

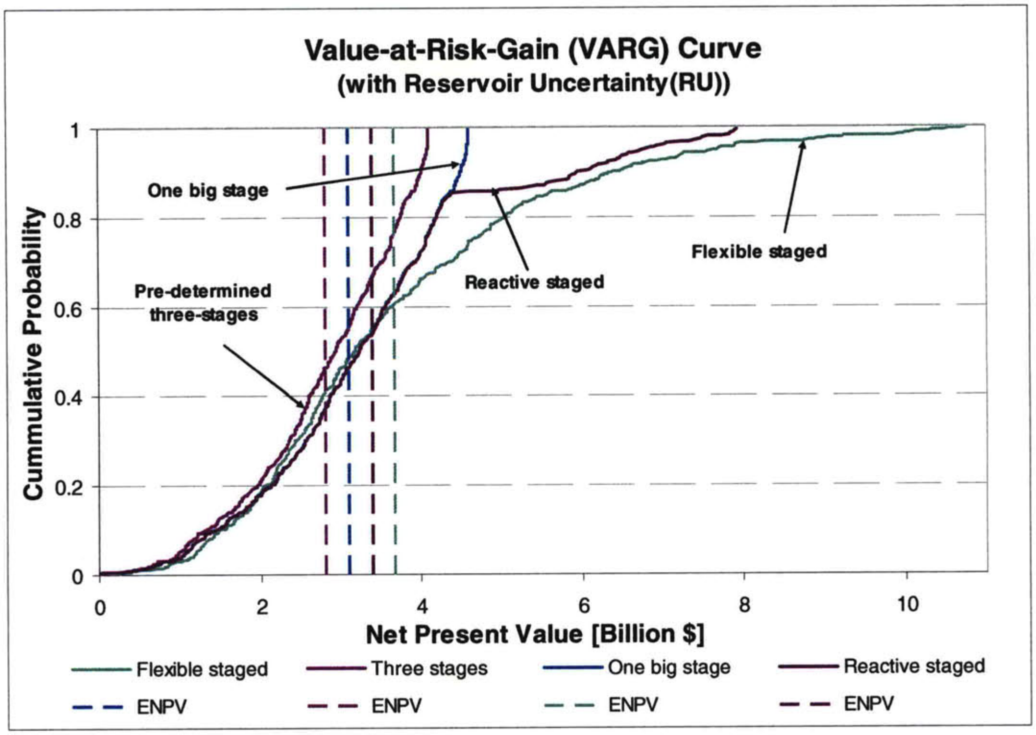


**Figure 66:** VARG curves for the four field development strategies (with RU only)

**Table 19:** Summary of economics statistics for the four strategies

| DEVELOPMENT STRATEGY | NPV ($, Billions) | | | | CAPEX ($, Billions) | | |
|---|---|---|---|---|---|---|---|
| | Expected | Minimal | Maximal | Standard Deviation | Expected Total | Minimal Initial | Maximal Eventual |
| One big Stage | 3.11 | 0.02 | 4.60 | 1.11 | 2.76 | 2.76 | 2.76 |
| Pre-determined three stages | 2.81 | 0.03 | 4.10 | 0.97 | 3.12 | 1.14 | 3.12 |
| Flexible staged | 3.66 | 0.25 | 10.76 | 2.01 | 3.88 | 2.25 | 10.05 |
| Reactive staged | 3.40 | 0.02 | 7.93 | 1.62 | 3.15 | 2.76 | 5.52 |

In order determine whether the differences between the ENPVs are statistically significant, we apply a t-test to conduct pairwise comparison of the ENPVs for the four strategies. This will give us statistical confidence regarding the differences between ENPVs. Let us represent these four strategies in terms of strategy A, B, C, and D.

- Strategy A: One big stage development
- Strategy B: Pre-determined three-stage development
- Strategy C: Flexible staged development
- Strategy D: Reactive staged development

The t-test assesses whether the mean of two groups are statistically different from each other. Table 20 shows the t-test results. The numbers represent the probability that the two samples have the same mean, which are all less than 5%. Therefore, statically we can conclude that: $ENPV_C > ENPV_D > ENPV_A > ENPV_B$.

**Table 20:** Pairwise t-test for the expected NPVs for the four strategies

| Probability that two samples have the same mean | A | B | C | D |
|---|---|---|---|---|
| A | | 4.71E-05 | 1.81E-06 | 3.99E-03 |
| B | | | 7.42E-14 | 9.88E-10 |
| C | | | | 3.73E-02 |
| D | | | | |

*(t-test type: same sample size, unequal variance, two-tailed)

**Discussions:**

Based on the comparisons of VARG curves and the summary of economics statistics in Figure 66 and Table 19, we have the following observations:

- The flexible staged development strategy outperforms the other three strategies. First, it significantly improves the project's ENPV (e.g., 18% improvement over one big stage). Secondly, the initial stage with smaller capacity reduces downside risks in reserve estimates (e.g., improves minimal NPV). Thirdly, the flexibility to add stage(s) allows this strategy to capture upside opportunity in reservoir uncertainty. For example, the maximal NPV of flexible staged deployment is 134% higher than the maximal NPV of one big stage strategy.

- The pre-determined three-stage strategy is the poorest choice in this case study. There are several reasons for this: First, the facilities with small capacity (33% of the one big stage) lose the economies of scale, thus, this strategy has higher per unit capacity CAPEX than strategy A. Secondly, this strategy phases the three identical stages over time in a deterministic way and production reaches a plateau in three steps. Thus, this strategy is penalized by the delayed peak production (entailing delayed revenue) compared to one big stage (faster ramp-up). Furthermore, although the pre-determined three staged strategy assumes a 90% learning factor for CAPEX due to the repetition of the same stage, the learning benefit is overwhelmed by the diseconomies of scale and delayed peak production.
- The single big stage development strategy (A) is used as a baseline case (rigid design without flexibility) for comparison. Due to economies of scale, it performs better (e.g., higher ENPV) than the pre-determined three-stage strategy. However, due to the rigid design and capacity constraint (100% capacity), it can not respond to the upside opportunities in reservoir uncertainty, therefore, significant amount of value is left unexploited. This can be seen by the sharp vertical rise in the VARG curve for this strategy.
- The reactive staged strategy (D) builds on the one big staged strategy (A). It responds to reservoir uncertainty in a reactive way. Because there is no designed flexibility in the initial stage, it is more expensive to add an additional stage than the flexible staged strategy. Furthermore, the reactive strategy has a capacity constraint (maximal 200% capacity in total) due to infrastructure limits in the initial design. In contrast, the flexible staged strategy does not have capacity limits, and is more adaptive to reservoir uncertainty and allows to add capacity in the future. Figure 66 shows that the VARG curve of the reactive strategy starts the same as the one big stage but departs later on to capture upside in reservoir uncertainty by adding an additional stage with 100% capacity. In part, the location of the "knee" in the VARG curve is determined by the reactive decision rule (Add a second stage with 100% capacity if $\Delta t > 450$). However, it cannot capture as much upside opportunities as the flexible staged strategy due to its capacity

limit and higher cost of expansion. Thus, the VARG curve of the reactive staged strategy falls in between the VARG curves of the one big stage and flexible staged strategies.

In summary, the flexible staged strategy performs best under reservoir uncertainty, and it improves the project's expected NPV by reducing downside risks and capturing upside opportunities. Furthermore, the flexible staged strategy starts with a small platform (75% capacity) and thus it reduces the project' exposure to risk in the initial investment. However the flexible strategy is also potentially the most complex to implement and requires constant monitoring of the exercise conditions.

### 6.4.2 Simulations with RU and FU

In the second step, we turn on facility uncertainty and simulate the four strategies under both reservoir and facility uncertainties. The simulation results are shown in Figure 66 and Table 21, respectively. Compared to the simulation results with reservoir uncertainty only, facility uncertainty reduces the NPV for all four strategies by a similar magnitude (~5% reduction on ENPV) and does not change the shape and rank orders of VARG curves for the four strategies.

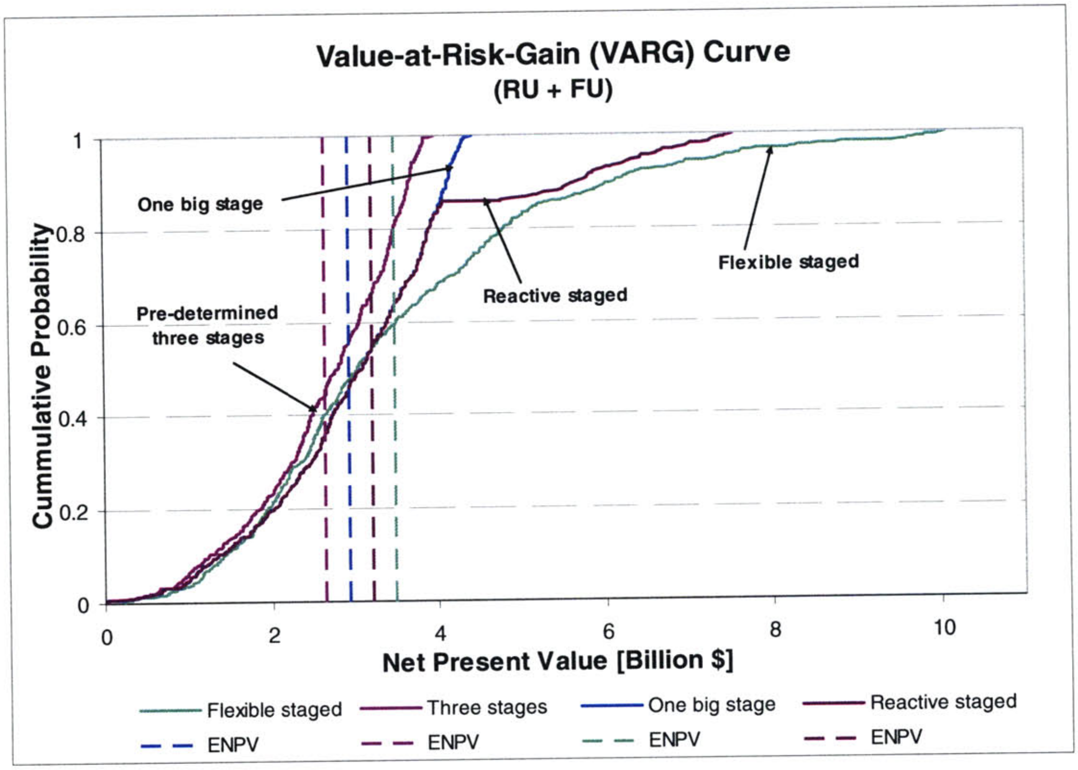


**Figure 67:** VARG curves for the four field development strategies (with RU + FU)

**Table 21:** Summary of economics statistics for the four strategies (with RU + FU)

| DEVELOPMENT STRATEGY | NPV ($, Billions) | | | | CAPEX ($, Billions) | | |
|---|---|---|---|---|---|---|---|
| | Expected | Minimal | Maximal | Standard Deviation | Expected Total | Minimal Initial | Maximal Eventual |
| One big Stage | 2.93 | -0.01 | 4.42 | 1.02 | 2.76 | 2.76 | 2.76 |
| Pre-determined three stages | 2.64 | 0.01 | 3.96 | 0.90 | 3.12 | 1.14 | 3.12 |
| Flexible staged | 3.49 | 0.23 | 10.07 | 1.91 | 3.88 | 2.25 | 10.05 |
| Reactive staged | 3.21 | -0.01 | 7.53 | 1.51 | 3.15 | 2.76 | 5.52 |

## 6.4.3 Simulations with RU, FU, and MU

In the third step, we turn on market uncertainty on crude oil prices and simulate the four strategies under reservoir, facility, market uncertainties. Figure 68 and Table 22 shows the simulation results. The decision rule is similar to previous one with reservoir uncertainty as shown in Figure 62, except we now add $30 per barrel as the minimal crude price for exercising flexibility (i.e., adding additional stages). In other words, even when a reserve condition is satisfied for adding additional stages, the triggering condition will be disabled if the crude price is less than $30 per barrel. Compared to the simulation results with reservoir uncertainty only, market uncertainty extends the NPV distribution for the four strategies and the differences between the four strategies appear to diminish (partially due to the extended scale in the horizontal axis); however, the rank order (e.g., ENPVs) of four strategies remain the same. The reasons that the market uncertainty brings the VARG curves of the four strategies closer together and improves ENPVs for all four strategies are as follows:

- The implementation of flexibility takes time (1~2 years). When market conditions appear favorable (e.g., high crude oil price), the decision rule will be triggered to exercise flexibility, but it will take several years for the flexibility to get implemented (such as building a new platform to increase production capacity). When the flexibility is implemented, the market conditions may already have evolved into a different state. Therefore, the time lag between perceived market opportunity and availability of implemented flexibility diminishes the advantage of flexible strategies. This is one of the main differences between real options in projects and financial options, which can be exercised and realized instantaneously. Perhaps, a more effective (or complementary) way to handle volatile market uncertainty is using a price hedging strategy.
- Furthermore, the market uncertainty model assumes a positive mean drift rate (on average 2% increase annually for oil price), thus, the overall NPV is higher than the results without market uncertainty.
- Finally, once the market uncertainty is turned on, reservoir and facility availability uncertainties are overwhelmed. As a result, the differences (or features such as the "knee" for the reactive strategy) between VARG curves are diluted. The VARG curves appear to get closer together. Market crude oil price becomes the dominant uncertainty affecting the shape of all VARG curves.

For the flexible staged strategy, both market and reservoir uncertainties are taken into account in the decision rule for the flexible staged strategy. We assume the minimal crude oil price for exercising flexibility (i.e., adding a stage) is $30 per barrel.

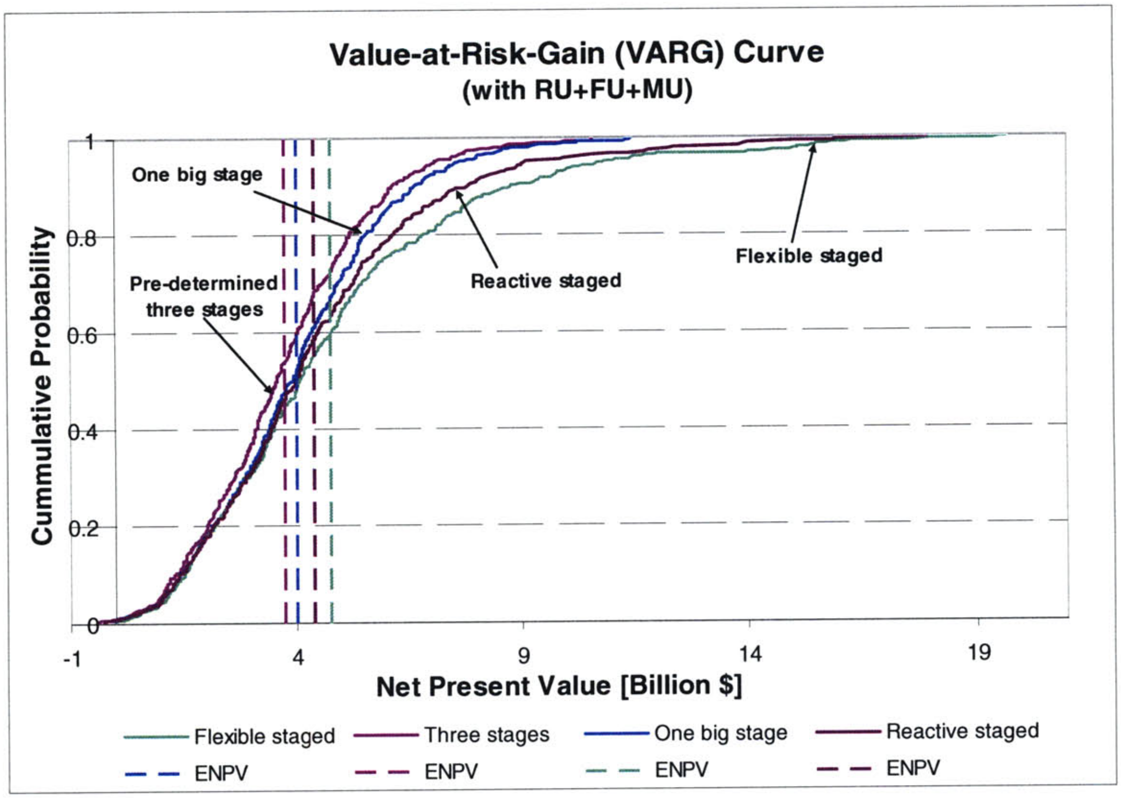


**Figure 68:** VARG curves for the four field development strategies (with RU + FU + MU)

**Table 22:** Summary of economics statistics for the four strategies (with RU + FU + MU)

| DEVELOPMENT STRATEGY | NPV ($, Billions) | | | | CAPEX ($, Billions) | | |
|---|---|---|---|---|---|---|---|
| | Expected | Minimal | Maximal | Standard Deviation | Expected Total | Minimal Initial | Maximal Eventual |
| One big Stage | 4.01 | -0.26 | 11.41 | 2.07 | 2.76 | 2.76 | 2.76 |
| Pre-determined three stages | 3.72 | -0.42 | 10.56 | 1.95 | 3.12 | 1.14 | 3.12 |
| Flexible staged | 4.76 | -0.01 | 19.69 | 3.24 | 3.87 | 2.25 | 10.05 |
| Reactive staged | 4.41 | -0.26 | 17.93 | 2.76 | 3.15 | 2.76 | 5.52 |

## 6.5 Sensitivity Analysis

The simulation results of this case study depend on the assumptions and parameters in the integrated models, the uncertainty models and the decision rule. A complete and in-depth sensitivity study of all model parameters may go beyond the scope of this thesis, therefore, we will illustrate the sensitivity of the results (e.g., VARG curves, ENPVs) to three selected key parameters.

There are two types of sensitivity analyses: one is global sensitivity analysis, in which we modify the parameters from the nominal values over a wide range to see when and how the rank order of the VARG curves changes (Hauser and de Weck, 2007); the other is local sensitivity analysis, in which we introduce a small perturbation to the parameters and examine the amount of change of the project's economics statistics (e.g., ENPV, minimal and maximal NPV). The rank order of VARG curves depends on many factors, such as assumptions and parameters in the screening models, uncertainty models, and decision rules. Here, we study the sensitivity of the flexible staged strategy on the following three parameters:

- *The cost of options*: In the flexible staged strategy, we assume the cost of option is 10% of the platform cost in the initial stage (with 75% capacity).
- *The benefit of options*: One benefit of flexible options is a CAPEX reduction for future stages. We assume the future CAPEX is 90% (parameter *m*) of its nominal CAPEX without flexibility.
- *The timing of enabling the exercising of flexibility:* In the flexible staged strategy, we assume the starting year of when flexibility can be exercised is year 3.

In this sensitivity study, we will vary these three parameters from their nominal values. The sensitivity analysis is based on the simulations with reservoir uncertainty only.

### 6.5.1 Global Sensitivity Analysis

**(1) Global sensitivity on the cost of options**

Table 23 shows the sensitivity on the cost of options for the flexible staged strategy. The cost of options is expressed as a percentage of the initial platform cost (subsea and well cost are excluded). By varying the cost of options, we re-run the simulations for the flexible staged strategy, we obtain different the VARG curves, and then record their associated metrics. For comparison purpose, the results of the reactive staged (D) and one big stage strategy (A) are also shown in this table. The 10% cost of the real option is the nominal value. From Table 23, we can see that the rank order of the ENPVs starts to cross over when the cost of expansion option increases to 40%. For example, the ENPV of the flexible staged strategy is still higher than the ENPV of the reactive staged strategy when cost of the option is 30%, but slightly lower when it is 40%. The ENPV of the flexible staged strategy remains higher than the one big stage even when the cost of the option increases up to 60%.

**Table 23:** Global sensitivity on the cost of options for the flexible staged strategy

| | **Flexible staged** | | | | | | | | **Reactive staged** | **One big stage** |
|---|---|---|---|---|---|---|---|---|---|---|
| Cost of option (% of initial 75% capacity platform cost) | 0% | 5% | **10%** | 20% | 30% | 40% | 50% | 60% | | |
| Cost of option (% of the CAPEX for One big stage) | 0.0% | 1.5% | **2.9%** | 5.9% | 8.8% | 11.7% | 14.7% | 17.5% | | |
| **ENPV (Bn$)** | 3.75 | 3.70 | **3.66** | 3.57 | 3.47 | 3.38 | 3.29 | 3.19 | 3.40 | 3.11 |
| **Min NPV (Bn$)** | 0.34 | 0.30 | **0.25** | 0.17 | 0.08 | 0.00 | -0.09 | -0.18 | 0.02 | 0.02 |
| **Max NPV (Bn$)** | 10.85 | 10.80 | **10.76** | 10.66 | 10.52 | 10.47 | 10.37 | 10.27 | 7.93 | 4.60 |

### (2) Global sensitivity on the benefit of option

Table 24 shows the global sensitivity of NPV on the benefit of options (i.e., CAPEX reduction on future stages) for the flexible staged strategy. Table 24 shows that as we increase the benefit of the option from 100% (no benefit of option) to 80% (CAPEXs of future stages are 80% of their nominal CAPEXs), the ENPV increases by 5.6%. Even when there is no benefit of option (i.e., 100%) on CAPEX reduction, the flexible staged strategy still performs better than the one big stage and the reactive staged strategies. This is because the flexible staged strategy has other benefits (such as flexibility to add more stages) that other strategies do not have. Even when there is an initial upfront cost of flexibility, and the development time and cost of future flexible stages are the same as in the inflexible strategies, the flexible staged strategy still outperforms the reactive and the one stage strategy.

**Table 24:** Global sensitivity on the benefit of option for the flexible staged strategy

| | Flexible staged | | | | | Reactive staged | One big stage |
|---|---|---|---|---|---|---|---|
| **Benefit of option** (% CAPEX compared to a new or reactive development) | 100% | 95% | **90%** | 85% | 80% | | |
| **ENPV (Bn$)** | 3.56 | 3.61 | **3.66** | 3.71 | 3.76 | 3.40 | 3.11 |
| **Min NPV (Bn$)** | 0.26 | 0.26 | **0.25** | 0.26 | 0.26 | 0.02 | 0.02 |
| **Max NPV (Bn$)** | 10.22 | 10.49 | **10.76** | 11.00 | 11.24 | 7.93 | 4.60 |

### (3) Global sensitivity on the timing of enabling the exercising of flexibility

Table 25 shows the global sensitivity on the timing of enabling the exercising of flexibility (i.e., CAPEX reduction on future stages) for the flexible staged strategy. As shown in Figure 69, as the starting time to exercise flexibility increases from 0 to 7 years, the ENPV increases up to an optimal value at year 3, and then decreases. However, the maximal NPV continuously decreases as the waiting time increases. There are two competing forces to drive the ENPV:

- The longer we wait, the more reliable the reserve estimate will be (presumably); thus, the decision rule is more likely to make correct decisions.
- On the other hand, the longer we wait, the less value a project can capture due to the delayed revenue and the discount effects on the future revenues.

Therefore, there is a balanced timing on exercising flexibility. It appears that year 3is the optimal timing for enabling the exercising of flexibility. In regards to the maximal NPV, the continuously decreasing trend represents a loss of opportunity by delaying flexibility. Table 25 shows that the ENPV of the flexible strategy becomes less than the ENPV of the reactive strategy when the time to first enable flexibility increases to 6 years.

**Table 25:** Global sensitivity on the timing of enabling exercising flexibility for the flexible staged strategy

| | Flexible staged development strategy | | | | | | | | Reactive staged | One big stage |
|---|---|---|---|---|---|---|---|---|---|---|
| **Time** (years when flexibility can first be exercised) | 0 | 1 | 2 | **3** | 4 | 5 | 6 | 7 | | |
| **ENPV (Bn$)** | 3.45 | 3.51 | 3.59 | **3.66** | 3.57 | 3.47 | 3.38 | 3.30 | 3.40 | 3.11 |
| **Min NPV (Bn$)** | -0.32 | -0.28 | 0.24 | **0.25** | 0.26 | 0.26 | 0.26 | 0.26 | 0.02 | 0.02 |
| **Max NPV (Bn$)** | 11.12 | 10.91 | 10.91 | **10.76** | 10.06 | 9.47 | 8.91 | 8.36 | 7.93 | 4.60 |

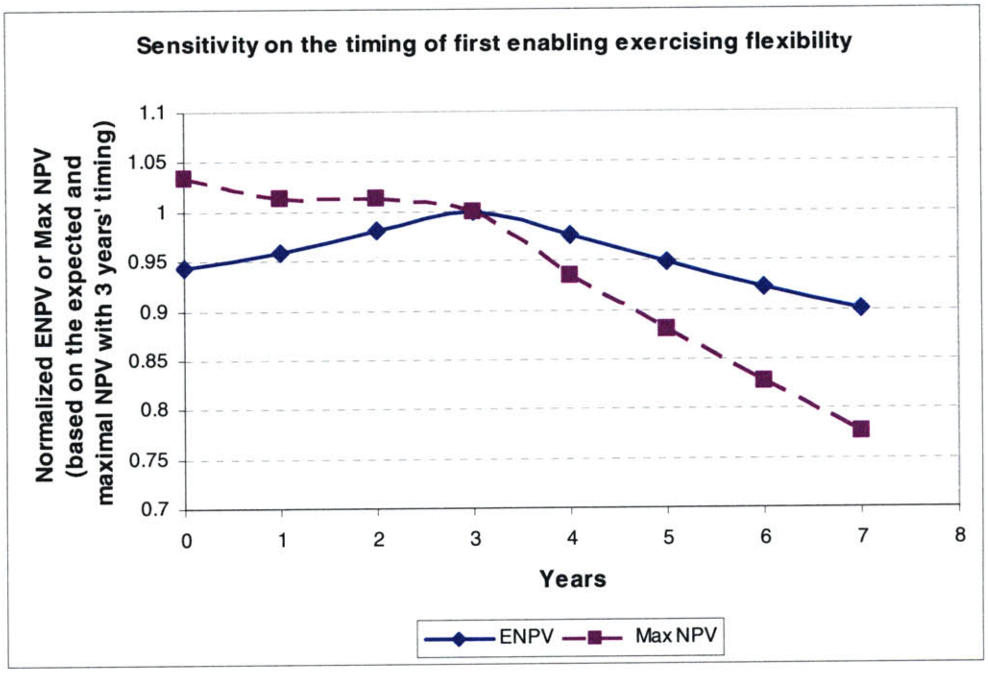


**Figure 69:** Sensitivity on the timing of first enabling exercising flexibility

## 6.5.2 Local Sensitivity Analysis

### (1) Local sensitivity on the cost of option

Equation 6-2 defines the parameter $\alpha_{\cos t\_of\_option}^{ENPV}(10\%)$ as the sensitivity of ENPV on the cost of option at the nominal value 10%. It represents how much ENPV will change if the *cost of option* increases 1% from its nominal value (central differencing).

$$\alpha_{\cos t\_of\_option}^{ENPV}(10\%) = \frac{ENPV[(10+\varepsilon)\%] - ENPV[(10-\varepsilon)\%]}{2\varepsilon} \qquad \text{[Eq. 6 - 2]}$$

where $\varepsilon$ is a small perturbation from the nominal value 10%. If we select $\varepsilon$ as 2 percent, we can run simulations based on 12% and 8% cost of options and then evaluate the local sensitivity around the nominal value:

$$\alpha_{cost\_of\_option}^{ENPV}(10\%) = \frac{ENPV(12\%) - ENPV(8\%)}{12-8} = \frac{3.6398 - 3.6769}{4} = -0.0093 \text{ (Bn \$)}$$

Thus, the local sensitivity $\alpha_{cost\_of\_option}^{ENPV}(10\%)$ tells us how the much the ENPV changes if the cost of option changes 1% from its nominal value 10%. The local sensitivity analysis provides a way to compare the sensitivities of the ENPV with respect to various model assumptions.

**Table 26:** Local sensitivity on the cost of option

| | Flexible staged | | |
|---|---|---|---|
| Cost of option (% of initial 75% capacity platform cost) | 8% | **10%** | 12% |
| ENPV (Bn$) | 3.6769 | **3.6643** | 3.6398 |
| Min NPV (Bn$) | 0.2725 | **0.2532** | 0.2380 |
| Max NPV (Bn$) | 10.7731 | **10.7590** | 10.7347 |

### (2) Local sensitivity on the benefit of option

Similarly, we can define the parameter $\alpha_{benefit\_of\_option}^{ENPV}(90\%)$ as the sensitivity of ENPV on the benefit of option at the nominal value 90%. It represents how much ENPV will change if the *benefit of option* increases 1%.

$$\alpha_{benefit\_of\_option}^{ENPV}(90\%) = \frac{ENPV[(90+\varepsilon)\%] - ENPV[(90-\varepsilon)\%]}{2\varepsilon} \qquad \text{[Eq. 6 - 3]}$$

where $\varepsilon$ is a small perturbation from the nominal value 90%. If we select $\varepsilon$ as 2 percent, we can evaluate the local sensitivity around the nominal value (90%):

$$\alpha_{benefit\_of\_option}^{ENPV}(90\%) = \frac{ENPV(92\%) - ENPV(88\%)}{92-88} = \frac{3.6384 - 3.6781}{4} - 0.0099 \text{ (Bn \$)}$$

**Table 27:** Local Sensitivity on the benefit of option

| | Flexible staged | | |
|---|---|---|---|
| Benefit of option (% CAPEX compared to a new or reactive development) | 92% | **90%** | 88% |
| ENPV (Bn$) | 3.6384 | **3.6643** | 3.6781 |
| Min NPV (Bn$) | 0.2553 | **0.2532** | 0.2553 |
| Max NPV (Bn$) | 10.6554 | **10.7590** | 10.8505 |

The ENPV does not appear to be very sensitive to either the cost or benefit of the option. This confirms the result of the global sensitivity analysis.

## 6.6 Summary

This chapter addresses Quadrant C (single reservoir and multiple facilities) of the problem landscape (Figure 58) through a case study about the development of a large oil field. Four development strategies, namely one big stage, pre-determined three staged, flexible staged, and reactive staged development strategies, are modeled and simulated under multiple domain uncertainty. The flexible staged strategy outperforms other three strategies in the following ways: it improves ENPV 17.7% over the one stage strategy (under reservoir uncertainty); it has marginal improvement on minimal NPV but has 134% improvement on maximum NPV. The reactive staged strategy ranks second as it cannot capture as much upside gain as the flexible staged strategy because of the 200% total capacity constraint. The pre-determined three stage strategy is the worst strategy among the four due to penalty of the diseconomies of scale and delayed peak oil production. By sequentially turning on reservoir, facility availability, and market uncertainty, we observe how VARG curves change. Facility uncertainty reduces NPV for all strategies by a similar magnitude. Market uncertainty extends both tails and dilutes the difference among strategies. By conducting global sensitivity analysis on several key parametric assumptions (e.g., cost of option, benefit of option, and timing of first exercising of flexibility), we see that the rank order of strategies is relatively robust and the flexible staged strategy remains superior to others over certain ranges of parametric values. The local sensitivity analysis provides a way to compare the sensitivities of the project's NPV on the parametric assumptions. The local sensitivity to the cost and benefits of options for CAPEX appears to be relatively low.

# Chapter 7: Case Study II: Tieback Flexibility in Deepwater Small Oilfield Development

## 7.1 Introduction

Increasingly, new discoveries are in deepwater (a couple thousand feet of water) and not in large monolithic reservoirs. The tieback for small oil field development scenarios generally involves a core field development and future tieback fields. A Central Processing Facility (CPF) is placed in the center of several core fields and serves as a hub. There are several conditions for such hub-based development: First of all, the core fields have to be close enough such that certain physical constraints can be satisfied (i.e., distance constraint due to pressure and flow assurance limitations). Secondly, the reserves in the core fields have to be large enough to justify the capital investment in the core fields' development. Thirdly, the field development plan is also constrained by the contractual time constraints for investment recovery with the host government, such as specified in a Production Sharing Agreement (PSA). The PSA also imposes time window constraints between announcement of a commercial discovery and development. As a result, development decisions cannot be deferred until all nearby potential fields have been completely explored and appraised. In practice, staged development of several hubs with tieback flexibility becomes an attractive strategy for a deepwater basin with many small oilfields. This case study corresponds to Quadrant B in Figure 58 of the problem landscape: the multiple reservoirs and single facility case. This case is inspired by a real ongoing development program at BP. Therefore, the identity of the fields is anonymized and the NPV results are normalized.

## 7.2 Problem Formulation

Tieback development of multiple oilfields generally involves two steps: 1) developing a hub (e.g., a CPF) for the core fields; 2) tieback of remote fields to the existing hub later in field operation when extra processing capacity becomes available. Figure 70 gives an example of tieback development, where one CPF is developed as a hub for three core fields, and other tieback fields can be tied back to the CPF if certain conditions are satisfied (i.e., spare capacity in the CPF). The connections can be production lines from reservoirs to facilities, water or gas injection lines from facilities to reservoirs, and service lines between reservoirs and facilities. Hence, the connections can be directional or two-way. For a generic representation, we assume all connections are two-way. This section proposes the concept of a "tieback option set" to define possible tieback scenarios in space or time.

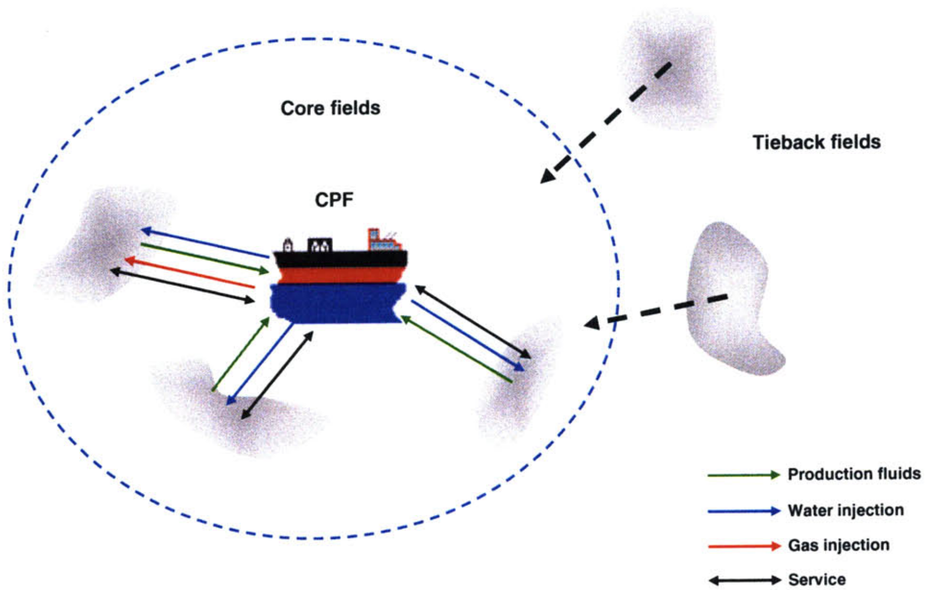


**Figure 70:** An illustration for tieback field development

The option set defines all the possible combinations of allowable tiebacks given a set of potential future developments. There are two dimensions in this problem. One is the spatial (configuration) combination, which determines which tieback fields are selected to tieback and how they are connected to existing infrastructures. The other is temporal, which determines when each tieback happens. The temporal combination involves path dependency[13]. For example, for the same spatial configuration, there are many ways to reach the configuration as reservoirs can be tied back to the facility in different sequences and at different times.

If both spatial and temporal combinations are considered, the tieback option set may include a large combinatorial space.

[13] Path dependency was addressed by Wang 2005. It is a general phenomenon for irreversible investment in engineering system designs and development.

- Spatial combinatorial space: This contains all possible combinations for a configuration in the spatial domain. It has two levels. The first level, the connectivity space defines whether reservoirs are connected to a facility directly or indirectly. The second level is the configuration space, which defines the routes for connections. Figure 71 shows the connectivity space and configuration space for connecting two out of three potential reservoirs. The number of connectivity combinations is $C_3^2 = 3$, which represents three columns. For each connectivity choice, there are three different configurations, which is shown as three rows.

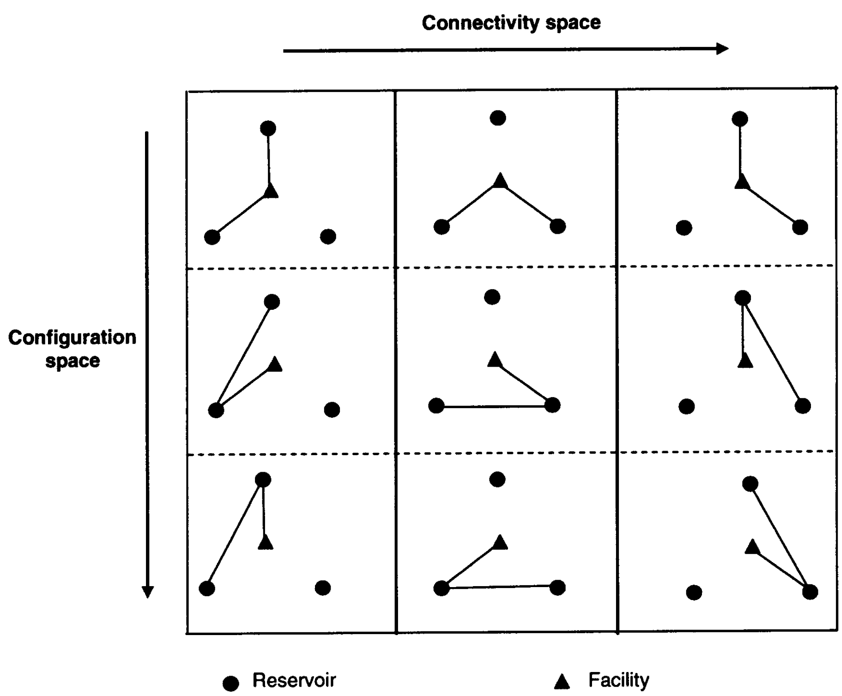


**Figure 71:** Connectivity and configuration spaces for connecting two out of three reservoirs to one facility

- Temporal combinatorial space: it defines all possible architectural evolutionary trajectories to reach a final configuration. Figure 72 shows four evolutionary trajectories within two time steps, given a final configuration. The final configuration is selected from the top left configuration in Figure 71. We can enumerate a temporal combinatorial space for each configuration shown in Figure 71. It may be possible to reduce the combinatorial space by introducing some rules, such as the distance constraints and number of connection constraints for a reservoir or facility.

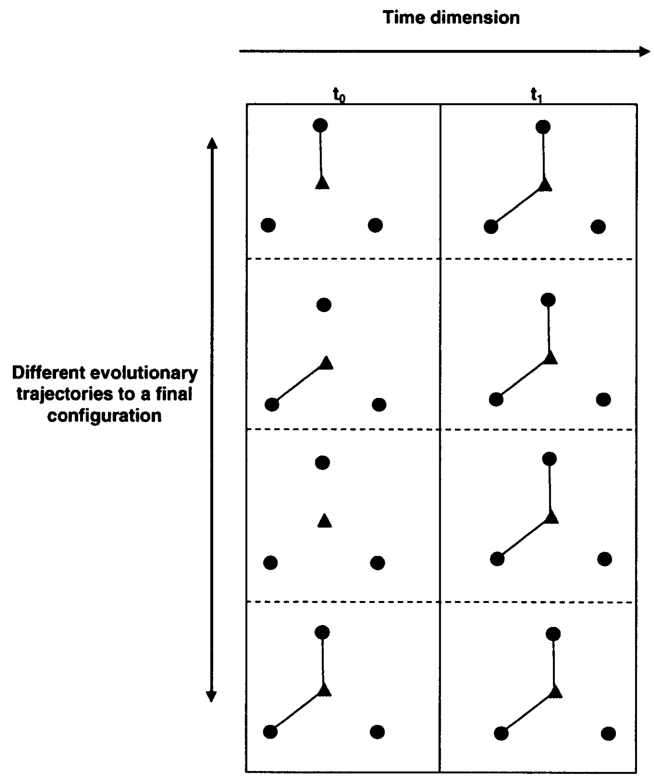


**Figure 72:** Evolutionary trajectories during two time steps for a final configuration

For example, for three tieback fields within four discrete time steps, there are a total of 8 ($C_3^0 + C_3^1 + C_3^2 + C_3^3 = 8$) different scenarios if we only consider the connectivity space. There are a total of 125 ($C_3^0 + (C_4^1)^1 C_3^1 + (C_4^1)^2 C_3^2 + (C_4^1)^3 C_3^3 = 125$) scenarios if both connectivity and temporal combinations are considered. There are much more than 125 scenarios if configuration combinations are taken into account, because there are different routing schemes (direct or indirect routing) given the same connectivity space (between facilities to reservoirs) as illustrated in Figure 71.

More generally, for $n$ number of tieback fields placed in $m$ discrete time steps, the total number of combination scenarios for the tieback option set can be calculated by the following formula[14]:

$$N = C_n^0 + m^1 C_n^1 + m^2 C_n^2 + m^3 C_n^3 + \cdots + m^i C_n^i + \cdots + m^n C_n^n \qquad \text{[Eq. 7-1]}$$

[14] This formula only considers the connectivity and temporal space. The configuration combination space is NOT taken into account. For the same connectivity scenario, there are multiple configurational combinations (or routing schemes). Therefore, the actual number of combinatorial space is much higher than what Equation 7-1 counts.

Clearly, the total number of combinations N grows very quickly as N is on the order of $m^n$. For six tieback reservoirs in a 15 year time period, there are more than 470 billion different tieback scenarios (assuming a time step at one year). It is computationally impractical to evaluate all possible configurations. Instead, we propose an approach to simulate possible tieback scenarios given a set of decision rules for flexible tieback, which automatically handles the spatial and temporal combinations. So, we only need to consider allowable spatial and temporal combinations upfront but let the decision rule-based simulation decide which combinations to select and when to exercise options in the tieback option set.

Figure 73 shows the field layout for a hydrocarbon basin. There is one CPF serving as a hub for connecting four core fields. There are six remaining fields, some of them are discovered and some of them are prospects. So, the spatial tieback option set includes all possible scenarios of selecting and connecting the remaining six tieback fields (i.e., R5~R10) to the CPF, ranging from no tieback at all to full tieback of six fields.

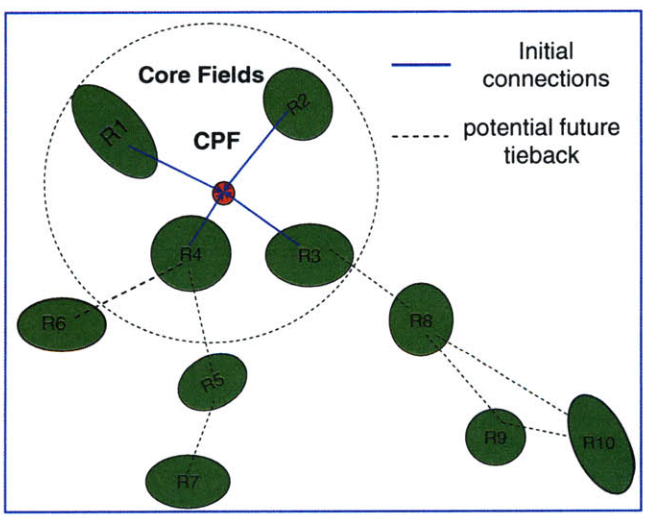


**Figure 73:** Field Layout for a hydrocarbon basin

There are two types of spatial tieback options in this case:

**(1) Unconstrained tieback option set**:

It assumes all six fields can all be tied back and there are no constraints on tieback. In other words, topside facilities and subsea architectures can accommodate four core fields plus six tieback fields. Considering the connectivity space, there are a total of 64 different tieback configurations for the unconstrained spatial tieback option set. Table 28 shows how the 64 unconstrained tieback scenarios are calculated. If the configuration space and temporal space are taken into account, the combinatorial space has much more than 64 configurations.

**Table 28:** Unconstrained tieback option set
(Connectivity space only)

| The number of tieback fields selected (among 6 potential tieback fields) | Numbers of scenarios (connectivity space only) |
|---|---|
| 0 | $C_6^0=1$ |
| 1 | $C_6^1=6$ |
| 2 | $C_6^2=15$ |
| 3 | $C_6^3=20$ |
| 4 | $C_6^4=15$ |
| 5 | $C_6^5=6$ |
| 6 | $C_6^6=1$ |
| Total | 64 |

**(2) Constrained tieback option set**:

Some of the fields cannot be tied back due to their distances from the CPF or other physical constraints such as capacity limits in the CPF, subsea infrastructure, and pipelines. Tieback could also be constrained by development sequences. For example, it might be preferred to tieback R5 before R7, because R7 can use R5 as an intermediate stop, and thus the existing pipelines from R5 to the CPF can be utilized. Furthermore, tieback may also be constrained by economic considerations. For example, a field may be too small to be tied back and developed economically due to the investment required for tieback infrastructure (i.e., subsea, pipelines, and wells). In summary, the potential constraints may include:

- Distance constraint due to physical limits (e.g., pressure drops)
- Capacity constraint on CPF, subsea infrastructure, and export pipelines
- Sequence constraint (or preference) due to geographical topology
- Economic constraint due to the tradeoff between tieback investment and benefit

In general, the constrained tieback option set is smaller than the unconstrained tieback option set. Therefore, in the field planning phases, multi-disciplinary teams need to work together to identify various constraints (i.e., reservoir, facility, and economic constraints) on tieback, which will reduce the search space for the following field development planning. However, for simplicity reason, we only consider the unconstrained tieback option set in this case study.

## 7.3 A Decision Rule for Tieback

In this section, we will prescribe a decision rule for flexible tieback. This decision rule determines when and how to exercise the embedded tieback flexibility as uncertainties unfold. Before we propose the decision rule, let us distinguish two concepts: deterministic tieback and flexible tieback. We found that practitioners do not generally make a clear distinction between these two concepts. In most cases, tieback means deterministic tieback in practice, but we propose flexible tieback in this case study. Table 29 shows the comparisons between the deterministic and flexible tiebacks.

**Table 29**: Differences between deterministic and flexible tieback

| | Tieback fields | Timing of developing tieback fields | Exercise tieback | Architectural and operational flexibility | Examples (based on Figure 73) |
|---|---|---|---|---|---|
| Deterministic Tieback | A limited number of pre-defined tieback configurations from the tieback option set | Deterministic | Deterministic | NO | Core fields + tieback R5 and R7 later |
| Flexible Tieback | A tieback option set is considered (numerous number of configurations) | Flexible | Stochastic (depending on uncertainty and decision rules) | YES | Core fields + tieback option set {R5, R6,..., R10} |

For flexible tieback, both the number of tieback fields and timing for exercising tiebacks are flexible. This keeps the option not to exercise any tieback fields if reserves in the core fields turn out to be much bigger than the initial estimate (thus no free CPF platform capacity would be available for tieback). Given the flexible tieback option, decision makers can postpone tieback decisions into the future when uncertainty unfolds. As a result, the flexible tieback reduces a project's initial CAPEX (compared to full-scale development) and its risk, and it also enables projects to capture upside opportunity by bringing in more resources through tiebacks. From an operational perspective, flexible tieback allows field operators to dynamically allocate facility capacity among multiple fields to optimize oil throughput. Therefore, flexible tieback provides both managerial and operational flexibility. In contrast, deterministic tieback makes a pre-commitment to one configuration among many possibilities in the tieback option set, it exposes a project to avoidable risks and constrains the project upside potential. Furthermore, decision makers have to select the initial set of fields that will be tied back which may turn out to be suboptimal (or even uneconomical) as reservoir and market uncertainties unfold.

For the flexible tieback strategy, we need a way to describe the conditions under which decision makers will take certain actions (i.e., tieback a field). However, in practice, some of these conditions are implicit knowledge in an organization (such as experience-based knowledge by senior managers and engineers). Even more challenging, the conditions are not static and they may evolve over time with an organization's acquisitions and transformations, changes in business environment, or emergence of new technology. Therefore, a complete and realistic description of the decision rules in a dynamic business context is a very challenging task. It would involve multiple disciplines, such as cognitive science, decision theory, management science, and engineering domain knowledge. In this study, we do not attempt to tackle this complex problem directly nor to suggest a decision rule for actual implementation. Instead we will propose a generic formulation of a decision rule to approximate organizational decision-making and demonstrate it through a specific flexible tieback case study. The idea is to use decision rules to simulate how decision makers may potentially respond to future uncertainty through exercising flexibilities (i.e., flexible tiebacks, capacity expansion, and operational flexibility).

A generic representation of decision rules can be formulated in terms of logic statements, such as a "IF… AND/OR … THEN …" statement. The following statement defines a generic decision rule set $\Psi$ :

A decision rule set $\Psi$ =

{

Take an initial ACTION;

For time $t = n_a{:}\ n_b$

Update the state vector $\hat{\vec{V}}(t)$ estimate;

IF $C_0\left(\hat{\vec{V}}(t)\right)$ THEN NO ACTION within time step $t$;

ELSEIF $C_1\left(\hat{\vec{V}}(t)\right)$ THEN take *ACTION 1*;

ELSEIF $C_2\left(\hat{\vec{V}}(t)\right)$ THEN take *ACTION 2*;

…

ELSEIF $C_k\left(\hat{\vec{V}}(t)\right)$ THEN take *ACTION k*;

...

ELSEIF $C_m\left(\hat{\vec{V}}(t)\right)$ THEN take *ACTION m*;

END

END

}

Note that actions 1, 2, ..., m are formulated in a way that makes them mutually exclusive.

where

$n_a$: the starting time step (or the starting year) that the action can be taken to exercise build-in flexibility (e.g., timing for exercising the tieback options).

$n_b$: the last time step (or year) that decisions for exercising flexibility can be made. The interval $[n_a\ n_b]$ is the time window for exercising flexibility.

$m$: the number of action branches (excluding the NO ACTION branch) in each time step.

$\vec{V}(t)$: a state vector which includes current reserve estimates $reserve(t)$ for the core fields and tieback fields, the market crude oil price $P(t)$, the tieback back option set $\Phi(t)$ at time $t$, and the operational flexibility parameter $\omega$. Note that $\omega$ takes several discrete values[15] to represent different ways of allocating the CPF's production capacity among multiple fields (operational flexibility). Thus, $\vec{V}(t)$ can be defined as follows:

$$\vec{V}(t)=\begin{bmatrix} reserve(t) \\ P(t) \\ \Phi(t) \\ \omega \end{bmatrix} \qquad \text{[Eq. 7 - 1]}$$

$\hat{\vec{V}}(t)$: the estimate of state vector $\vec{V}(t)$.

$C_k\left(\hat{\vec{V}}(t)\right)$: the condition is a function of the estimate of state vector $\hat{\vec{V}}(t)$, where $k = 1 \sim m$.

*ACTION k*: the action branch $k$, where $k = 1 \sim m$. There three types of ACTIONS in this case study:

[15] The value of 0, 1, and 2 corresponds to sequential, proportional, and watercut-based allocation schemes respectively.

- Strategic flexibility: actions to select and tie back one or several tieback fields to the existing CPF.
- Tactical flexibility: actions to expand the production capacity of the CPF.
- Operational flexibility: actions to dynamically allocate production capacity using different capacity allocation schemes (i.e., sequential, proportional, and watercut-based allocation schemes) among multiple fields. We denote this specific type of operational flexibility as Active Reservoir Management (ARM).

The decision rule set $\Psi$ pre-defines a set of conditions and action branches. However, the conditions ($C_k\left(\hat{V}(t)\right)$), the number of branches ($m$), the timing of exercising options ($n_a$, $n_b$) vary according to specific cases. Setting up a reasonable decision rule requires engineering knowledge and decision making experience. In this case study, we propose an initial decision rule based on some experience and a series of test runs. We then conduct sensitivity analysis to test the decision rule by varying some key parameters. The screening model provides a computational lab to experiment and fine tune these decision rules. The conditions in the decision rules are functions of the state vector estimated by decision makers, and the estimate of the state vector evolves over time. So, the decision rules provide a way to simulate possible decisions to be taken as human perception of uncertain variables evolves over time.

For the flexible tieback case illustrated in previously, depending on how the reserve estimates for the four core field evolve, there are two types of scenarios as shown in Figure 74.

a) If the total reserves of the core fields turn out to be much larger than the initial estimate, no additional tieback fields would be needed since there is no extra processing capacity available even with capacity de-bottlenecking. There is a potential to build a second CPF for the remaining six fields, but this case study only allows for one CPF. The tieback will not be exercised if the total reserves of core fields turn out to be bigger than a certain threshold. We leave it to future research to consider building a second dedicated CPF for tieback fields (i.e., R5~R10) if the reserves for the core fields and tieback fields both turn out to be large enough.

b) If the total reserves in the core fields turn out to be much smaller than the initial estimates, there is a need to bring in more reserves and to utilize the "free" capacity of the existing asset to make the current project economically viable. But tieback will not be exercised if the oil throughput reaches the platform's capacity. Therefore, even if there is a desire to bring in more resource from a reserve's perspective, tieback will not be exercised immediately due to the platform's capacity constraint. Finally, the reserves in tieback fields need to be large enough to be developed economically. In summary, the following three conditions have to be satisfied in order for tieback options to be exercised.

   - The estimated total reserve for the core fields is less than a threshold (i.e., 600 mmbbls).
   - The oil throughput is less than the platform's capacity. In other word, there is spare production capacity available for producing hydrocarbons from tieback fields.
   - The estimated reserves of the tieback fields are greater than a threshold (i.e., 30 mmbbls) to be developed economically. When multiple tieback fields are all economically viable options, the decision rule needs to decide which one to tieback first. Figure 75 shows (a) the evolution of reserves for tieback fields, and (b) the evolution of development cost per unit reserve, which is the normalized tieback cost (e.g., wells, drilling, and SURF cost) against the amount of reserve to be developed. If the tieback sequence is based on Figure 75 (a), decision makers will select the fields with largest reserves (R9). On the other hand, if the tieback sequence is based on Figure 75 (b), decision makers will select the fields with lowest development cost per unit reserve (R9). The outcomes of these two criteria is somewhat consistent if the underlying tieback costs do not vary much with respect to the size of tieback fields due to fixed cost of tieback. This case study uses (b) minimal development cost per unit reserve as the economic criterion to prioritize the tieback sequence. However, the physical criteria (e.g., prioritized routing of flows, maximum number of connections, maximum distance) for the tieback sequence are not taken into account in this case study. This is also an area for future research.

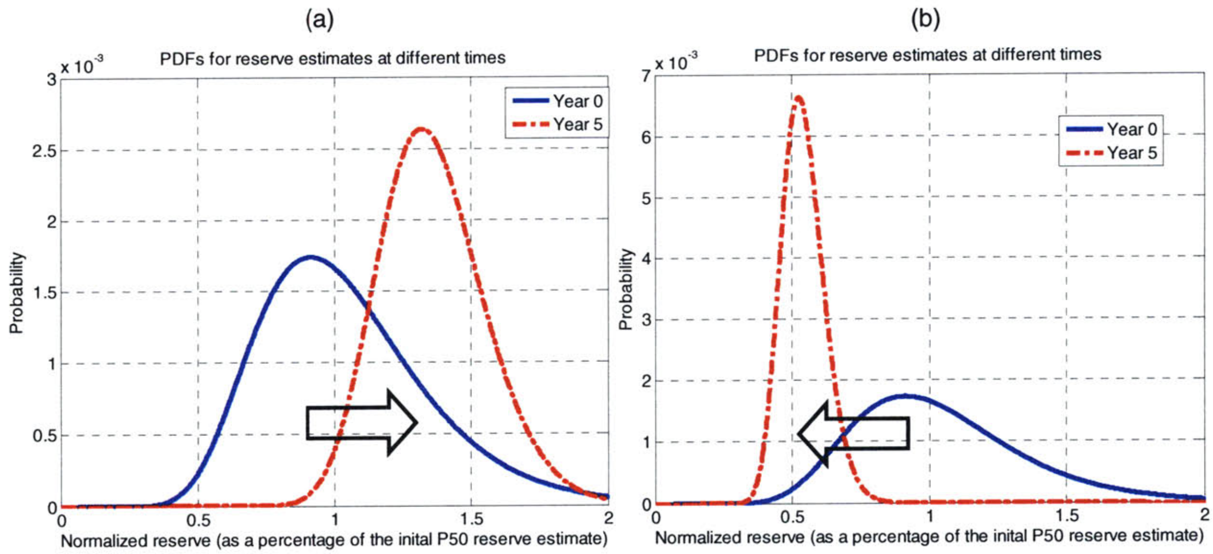


**Figure 74:** Two types of scenarios for the evolution of core reserve estimates

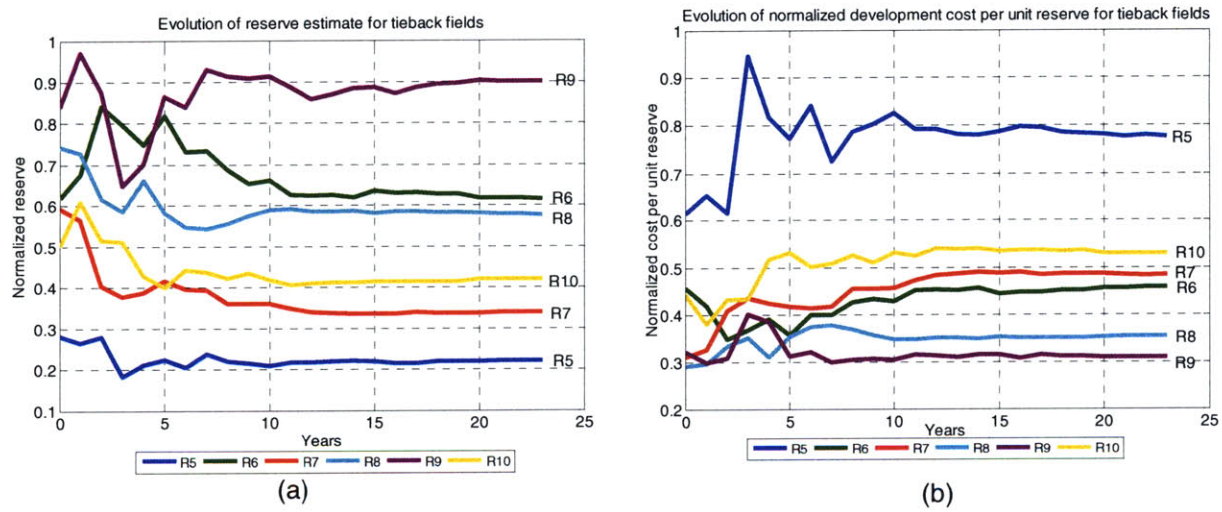


**Figure 75:** (a) Reserve evolution for six tieback fields; (b) development cost per unit reserve

Figure 76 shows a generic decision rule structure for a flexible tieback field development strategy. Three levels of flexibility – tieback flexibility, capacity expansion flexibility and Active Reservoir Management (ARM) flexibility – can be turned on or off in this decision rule. The conditions $C_k\left(\hat{\hat{V}}(t)\right)$ for exercising tieback and capacity expansion flexibility are critical in this decision rule. They are based on the estimate of the state vector $\vec{V}(t)$. There are two action branches (YES/NO) for tieback or capacity expansion flexibility. The threshold for exercising tieback or capacity expansion depends on each specific case.

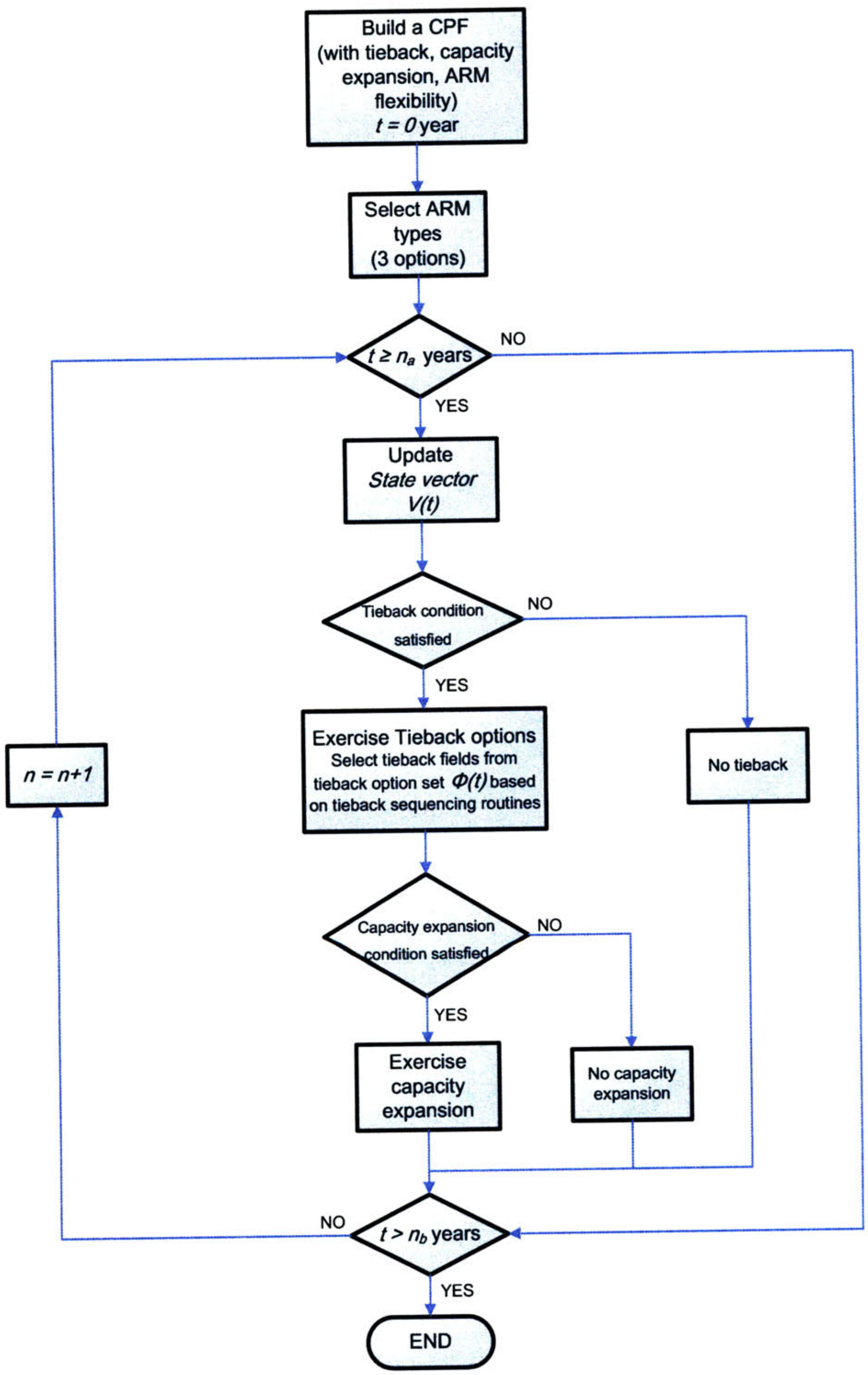


**Figure 76:** A generic decision rule for flexible tieback field development

A specific decision rule for the flexible strategy of this case study is illustrated as follows:

```
At Year 0
    Build a FPSO with 150 MBD crude production capacity (for P50 reserve estimates)
     • With tieback flexibility (assuming cost of option: 10% of initial SURF cost)
     • With capacity expansion flexibility (assuming no initial cost for this option)
     • Select Active Reservoir Management (ARM) flexibility (three types of options, no initial
       cost for this option)
    Set cap_exp_flag = 0;

For t = 3 to 10
   Update tieback option set (remove fields that have already been tied in);
   Update reserve estimates  for core fields and tieback fields;
   tieback_field  = INDEX(min( development cost / reserve ));
   IF  existing_reserve(t) ≤ Cap2reserve(q_oil,t) AND reserve of tieback reservoir i > 30
       THEN tieback tieback_field;

   ELSEIF existing_reserve(t) > Cap2reserve(q_oil,t) AND reserve of tieback reservoir i  > 30
       IF cap_exp_flag =0
          THEN expand platform capacity from 150 to 200 MBD;
                  tieback tieback_field;  set cap_exp_flag = 1;
       ELSEIF cap_exp_flag = 1
          THEN  tieback tieback_field;
       END
   END
END
```

There are several key elements for this decision rule:

- At year 0, a CPF with 150 MBD oil production capacity is built based on the reserve estimates (i.e., P50) for the four core fields. Firstly, the initial design has built in tieback flexibility. The cost of tieback flexibility is assumed as 10% of the initial SURF cost. Secondly, it assumes that there is some extra space available on the CPF for capacity expansion from 150 to 200 MBD. This decision rule assumes there is only one time expansion, and the parameter *cap_exp_flag* (1 for yes, 2 for no) indicates whether or not this option has been exercised. This decision rule assumes that there is no initial cost for capacity expansion flexibility or this flexibility comes "free" by assuming the operator can add additional decks and equipment on the CPF. However, the capacity expansion will require future CAPEX investment for adding the additional modules and processing equipment. It assumes that the cost per unit throughput for capacity expansion is the same as the initial CPF development cost per unit throughput. Thirdly, Active Reservoir Management (ARM) flexibility can be enabled at the beginning of each simulation.

- Between year 3 ($n_a$) to 10 ($n_b$), the decision rule will exercise tieback and capacity expansion flexibilities if the triggering conditions are satisfied. These conditions are based on the estimation of reserve and the oil throughput at time t. In each time step, the decision rule updates the tieback option set and eliminates the fields that have already been tied back. The decision rule will exercise the tieback option if the existing reserve[16] is less than a certain threshold calculated by a function *Cap2reserve*($q_{oil}$, *t*). This function[17] transforms a platform's oil production capacity into the amount of reserve the platform can produce within a limited time horizon. For example, the nominal reserve that a platform with 150 MBD oil production capacity can produce is 600 mmbls. The minimal amount of reserve for a field to be tied back is assumed as 30 mmbbls. This minimal reserve for tieback is used as an economical criterion for tieback, and the field with minimal development cost per unit reserve will be tied back first from the tieback option set.
- If the existing reserve is greater than a certain threshold while the tieback option is not empty, a one-time capacity expansion (i.e., from 150MBD to 200 MBD) will be exercised.
- If tieback causes the potential production or injection rates to exceed the infrastructure constraints (such as platform capacity), ARM routines (i.e., sequential, proportional, watercut-based allocation schemes) provide different ways to manage the flows rates among multiple fields.
- The conditions in this decision rule, such as minimal tieback reserves (30 mmbbls) and timing of enabling tieback flexibility ($n_a$= year 3), are not necessarily optimal and they are based on engineers' experience and trial and error. An "optimal" decision rule would depend on the specific cases and uncertainty models. In this case study, we will conduct sensitivity analysis on a few parameters in the decision rule.

The decision rules shown in this section is for the most flexible strategy (with tieback, capacity expansion, and ARM flexibility). The implementation of this decision rule allows to turn on or

[16] Existing reserve is the amount of estimated reserve being tied back to the CPF at time *t*.

[17] This function is not simply the designed oil production capacity multiplied by the remaining time (from $t$ to $t_{max}$) because the production cannot remain at the peak rate due to water break in later during production. This function is developed based on a nominal production profile.

off specific types of flexibility. For a rigid strategy, all three types of flexibility can all be turned off. In other word, no decision rule would be needed.

## 7.4 Simulation Framework

Figure 77 illustrates the overall simulation framework. In this case study, we use the integrated screening model that was developed in Chapter 4 to explore different field development strategies under multi-domain uncertainty. This simulation framework allows to evaluate a development strategy by gradually turning on the three types of uncertainty (i.e., reservoir, facility, and market uncertainties), thus, we can see the impact of uncertainty on the distribution of outcomes. Furthermore, this simulation framework enables us to construct strategies with the three levels of flexibility (e.g., strategic, tactical, and operational flexibilities) and then compare their performance under uncertainty. Overall, this simulation framework gives system architects and decision makers a computational laboratory to simulate and compare different field development strategies under multi-domain uncertainty.

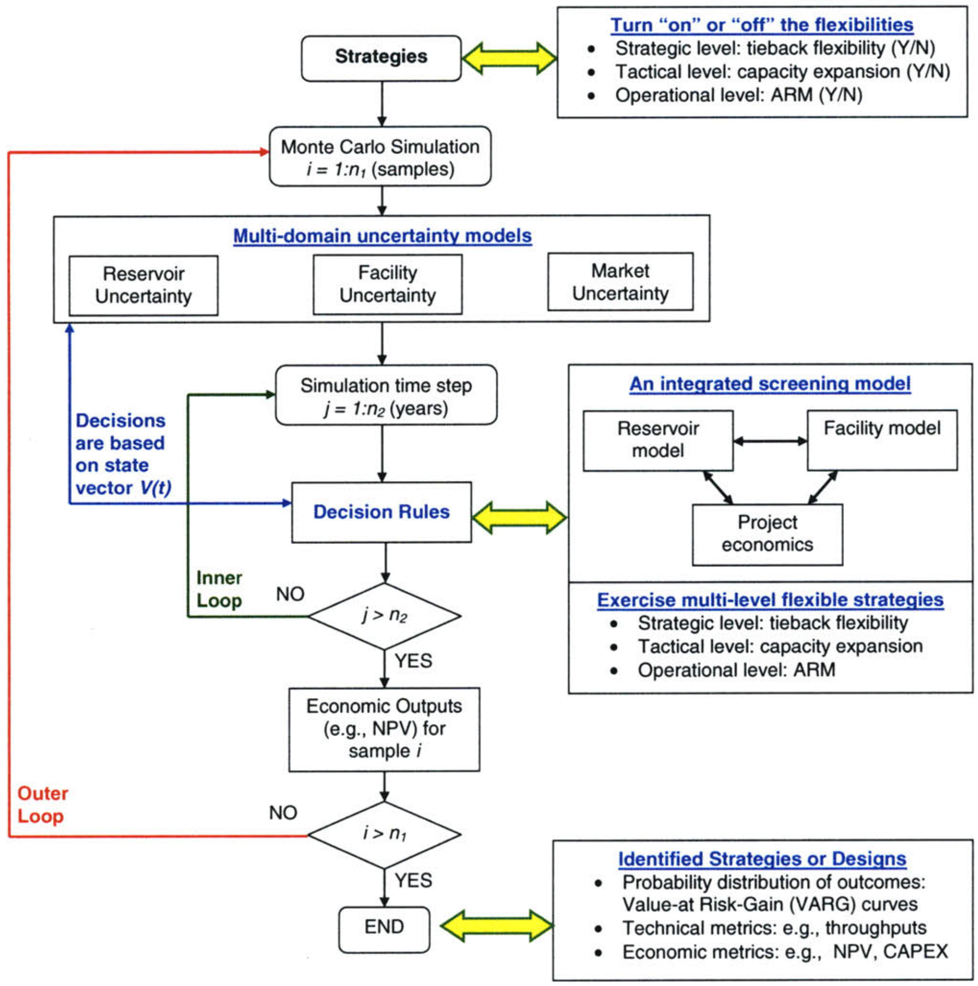


**Figure 77:** A simulation framework for screening strategies under multi-domain uncertainty

This simulation strategy includes two simulation loops:

- The outer loop is the Monte Carlo simulation loop. Before the simulation, a development strategy is constructed by turning on or off specific types of flexibility. At the beginning of each simulation step ($i = 1{:}\ n_1$), a combination sample for reservoir, facility, and market uncertainties is generated. For example, one sample combines three different instances of evolutionary paths for reserve estimates, facility availability, and crude oil prices over the lifecycle of the project. In this case study, we assume the sample size is 200 ($n_1$=200). Based on the simulation results, we found that the VARG curves are relatively smooth when $n_1$=200. However, the number of simulation needs to be determined by the desired confidence level on the simulation results.

- The inner loop simulates the production profile over time ($j = 1: n_2$ years) and calculates project economic outcomes given one combination sample for reservoir, facility, and market uncertainty. There is a decision rule within the inner loop which dynamically adjusts the field development or operations according to the estimate of the state vector $\vec{V}(t)$. Such dynamic adjustment in fact represents exercising flexibility at different levels (i.e., strategic, tactical, and operational flexibility). In general, the state vector $\vec{V}(t)$ includes the current uncertain variables (e.g., reserve, crude oil price), and the current field architecture (e.g., tieback option set, number of platforms, capacity). The decision rules are formulated and defined before simulation.

The decision rule provides a mechanism for the inner loop to interact with the outer loop, because the decision rule is based on an estimate of the state vector $\vec{V}(t)$, which is a combination of uncertain variables (outer loop) and current production (inner loop). For example, as reservoir production occurs, the estimates of reserves will be updated and potentially get closer to the true value. Once the decision rule exercises architectural flexibility (e.g., tieback a reservoir to the existing CPF), the reservoir model and facility model will be updated simultaneously and then the simulation continues. When one inner loop is completed, a set of economics metrics are produced, such as the project's NPV and CAPEX. When the outer loop is completed, a distribution of economic outcomes is obtained, such as the Value-at-Risk-Gain (VARG) curve. VARG is a cumulative distribution function of NPV, which gives a holistic view of project economic outcomes, such as expected NPV, downside risk, and upside gain.

In order to dynamically change field development plans and operations within the reservoir simulation loop (the inner loop), a reservoir profile generator was developed in this case study. Figure 78 shows the structure and functions of this profile generator. The inputs for this profile generator are dimensionless production profiles. There are two types of profiles: First, if a commercial reservoir simulation model is available, we can turn the unconstrained production profiles into dimensionless profiles, such as oil production rates as a function of cumulative oil produced. On the other hand, if a commercial reservoir model is not available, we can use the tank model[18] to simulate the unconstrained production. For the tieback case study with multiple fields, we can generate one unconstrained dimensionless production profile for each individual field. In each time step, the profile generator determines the oil/water/gas production rates by sampling the unconstrained production profiles according to cumulative oil produced. The injection rates are calculated based on material balance equations. The facility constraints (e.g., production capacity for oil/gas/water, injection capacity for water/gas) are applied after the capacity allocation logic has been applied as shown in Figure 78.

The right hand side of Figure 78 shows the simulation flow chart for the coupled reservoir-facility model. The first step in the simulation is to allocate (CPF) platform production capacity among multiple reservoirs. There are three types of allocation schemes available in the reservoir profile generator:

- **Sequential allocation**: This scheme allocates platform oil production capacity according to field development (e.g. tieback) sequences. In other words, the first producing field has the priority to fill the capacity even if it has higher watercut than other tieback fields that come online later (with lower watercut). Thus, this allocation scheme does not maximize the capacity utilization because more oil could have been produced earlier if a dynamic allocation schemes (watercut-based) is allowed. This scheme is referred to as having NO Active Reservoir Management (ARM) in this case study
- **Proportional allocation**: This allocation scheme fills CPF capacity with maximal production potential from all fields. If the total production (or injection) rates exceed the platform capacity, the rates are proportionally cut back according to the each reservoir's production potential.
- **Watercut-based allocation**: This allocation scheme optimizes oil throughput given the platform capacity constraints. In each simulation time step, platform production capacity is allocated according to each reservoir's water cut. The reservoir fluids with the lowest water cut are produced first. Essentially, this scheme allows dynamic allocation of platform capacity according to reservoir water cut and it provides operational flexibility. This scheme is interpreted as a type of operational flexibility – Active Reservoir

[18] The fidelity of tank model can be improved by using WOR and GOR correction coefficient.

Management (ARM). In practice, watercut-based allocation is applied by production engineers on platforms, and they optimize oil production through changing the flow rates (both production and injection rates) for multiple fields. In this case study, the difference between sequential allocation (no ARM) and water cut based allocation (ARM) is compared in terms of VARG curves.

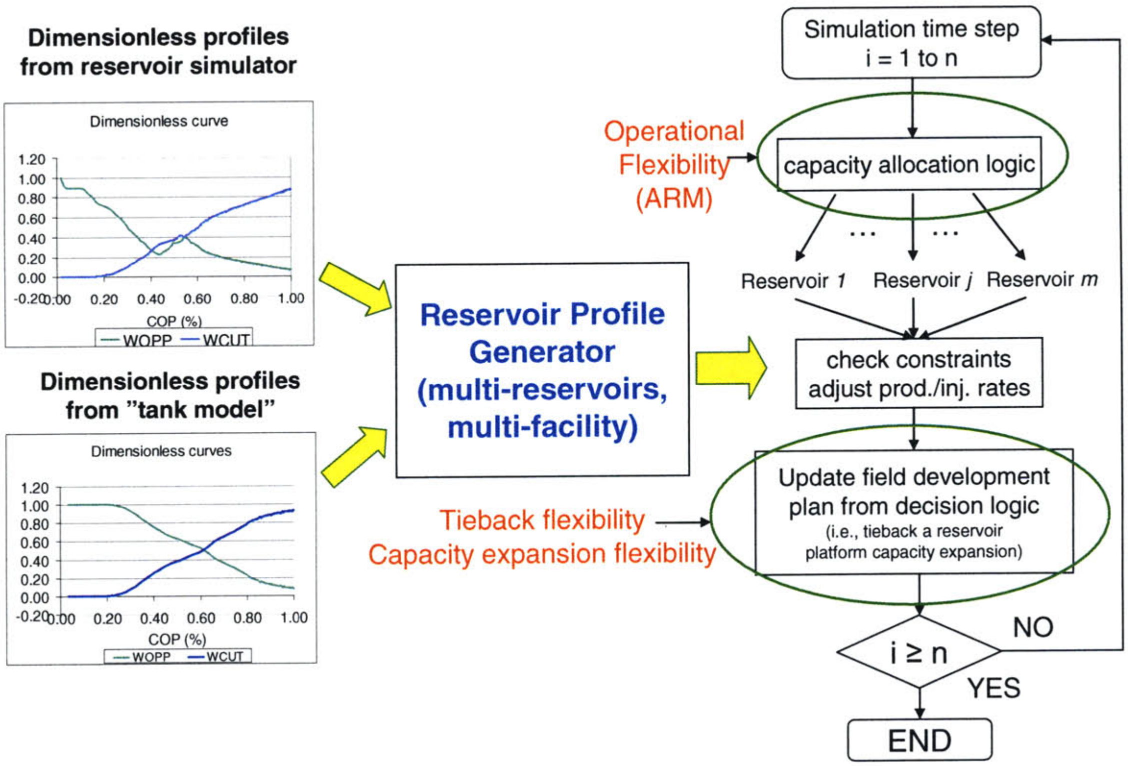


**Figure 78**: A reservoir profile generator

## *7.5 Simulation Results and Discussions*

In this case study, we will turn on reservoir, facility, and market uncertainty sequentially. Section 7.5.1 illustrates how to use a design of experiments approach to formulate a set of development strategies by turning on or off specific levels of flexibility, and then evaluate them under reservoir uncertainty. This systematic approach allows us to quantify the Value of Flexibility (VOF). In Sections 7.5.2 and 7.5.3, the same set of strategies is evaluated by turning on facility and market uncertainty sequentially.

### 7.5.1 Simulations with RU

In the previous sections and chapters, we introduced and discussed the various elements for enabling the simulation: the screening model, decision rules, the multi-domain uncertainty models, tieback option set, and simulation strategy. We are now ready to explore different field development strategies using the simulation framework. This case study implements the following three levels of flexibility:

- Strategic (inter-facility) flexibility: Tieback flexibility in this case study allows connecting fields from six tieback reservoirs when the following tieback conditions are satisfied: First of all, the platform has extra production capacity to handle additional fields. Secondly, the estimated reserves in the tieback fields are large enough to justify the investment (i.e., addition investment/ additional reserve > economic threshold). Thirdly, if the reserve estimates of the existing fields are much smaller than the initial estimate, it will also trigger to connect tieback fields to fill the platform's otherwise idle capacity.
- Tactical (intra-facility) flexibility: Platform capacity expansion flexibility is an example of intra-facility flexibility. In this case study, we assume the initial platform capacity is either 150 or 175 MBD. For the design with initial 150 MBD capacity, we assume that its capacity can be expanded from 150 to 200 MBD. For the design with initial 175MBD capacity, we assume that there is no capacity expansion flexibility.
- Operational flexibility: In this case study, operational flexibility particularly refers to Active Reservoir Management, such as dynamically allocating platform processing capacity for the streams of fluids from multiple reservoirs (see Section 7.4). In this case study, no ARM refers to sequential capacity allocation, while ARM refers to watercut-based capacity allocation.

Table 30 shows the cost of options for the three levels of flexibility. In this case study, we assume the cost of tieback flexibility is 10% of the initial SURF cost, but there is no initial cost for acquiring capacity expansion and ARM flexibilities. It is left as future work to model the cost of options in more detail. In Section 7.6, we conduct sensitivity analysis based on the assumptions on the cost of tieback flexibility and capacity expansion flexibility.

**Table 30:** Assumptions for cost of options (flexibilities)

| Levels of flexibility | Cost of options (flexibilities) |
|---|---|
| **Strategic: Tieback flexibility** | • Extra 10% of initial SURF cost<br>• Deferred tieback costs (wells, SURF) |
| **Tactical: Capacity expansion flexibility** | • No initial cost for having this option<br>• Deferred capacity expansion costs (assumed the same cost/capacity as initial platform capacity ) |
| **Operational: ARM flexibility** | • No extra capital cost involved (may incur extra OPEX, not yet considered in this case study) |

We can use Design of Experiments (DOE) to systematically compare and test the combinations of these flexibilities. The first step is to study eight development strategies with 150 MBD initial capacity. The second step is to study four development strategies with 175 MBD initial capacity.

**(1) Development strategies with 150 MBD Initial capacity**

Table 31 shows a full factorial experimental design matrix. Three levels of flexibility correspond to three factors. Each factor has two values: Y – with flexibility turned on, N—with flexibility turned off. So, there are a total of $2^3$ strategies. Each strategy is simulated with 200 samples of trajectories for reserve estimates. Different levels of flexibility in the decision rule will be enabled or disabled according to Table 31. Each strategy corresponds to not only one design but a family of designs with the same decision rule and the same initial configuration in each family. All 8 strategies have the same initial configuration: one 150 MBD CPF for the four core fields shown in Figure 73. For example, for strategy 8, even though three levels of flexibility are all enabled, some scenarios among 200 runs may not exercise the flexibility allowed by the strategy.

**Table 31:** Design of experiments for strategies 1~8 (with initial 150 MBD capacity)

| Flexibility type | Strategic (inter-facility) flexibility | Tactical (intra-facility) flexibility | Operational flexibility |
|---|---|---|---|
| | Tieback flexibility (Y/N) | Platform expansion flexibility (150→200 MBD) (Y/N) | Active reservoir management (Y/N) |
| Strategy 1 | N | N | N |
| Strategy 2 | N | N | Y |
| Strategy 3 | N | Y | N |
| Strategy 4 | N | Y | Y |
| Strategy 5 | Y | N | N |
| Strategy 6 | Y | N | Y |
| Strategy 7 | Y | Y | N |
| Strategy 8 | Y | Y | Y |

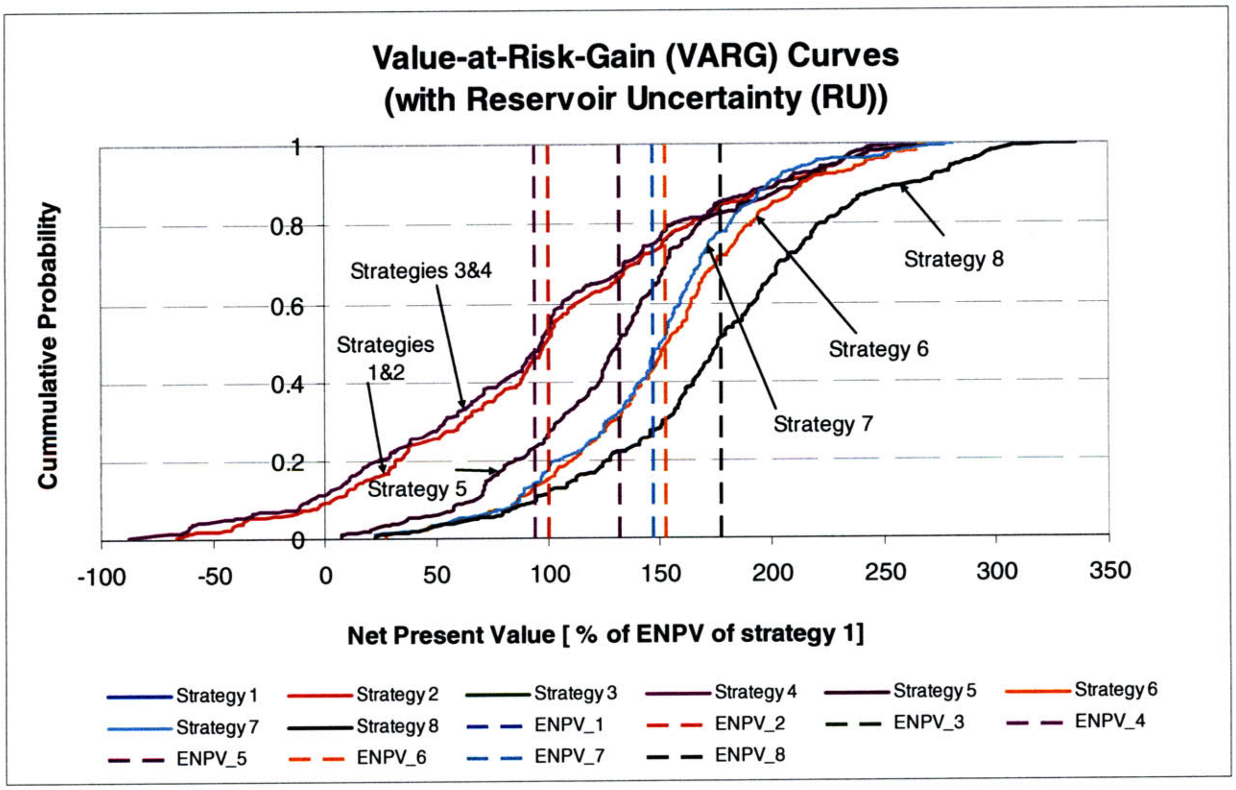


**Figure 79:** VARG curves for the strategies 1~8 under RU

**Table 32:** Summary of statistics for strategies 1~8 under RU

| | NPV (% of ENPV for strategy 1 ) | | | | CAPEX (% of expected CAPEX for strategy 1) | | | | Expected total reserve | Expected # of tiebacks |
|---|---|---|---|---|---|---|---|---|---|---|
| | Expected | Min | Max | σ(NPV) | Expected | Min | Max | Initial* | | |
| Strategy 1 | 100 | -66 | 251 | 74 | 100 | 100 | 100 | 64 | 100 | 0.0 |
| Strategy 2 | 100 | -66 | 255 | 74 | 100 | 100 | 100 | 64 | 100 | 0.0 |
| Strategy 3 | 94 | -88 | 262 | 77 | 102 | 100 | 109 | 64 | 100 | 0.0 |
| Strategy 4 | 94 | -88 | 260 | 77 | 102 | 100 | 109 | 64 | 100 | 0.0 |
| Strategy 5 | 132 | 7 | 266 | 54 | 138 | 104 | 172 | 66 | 148 | 2.5 |
| Strategy 6 | 152 | 27 | 276 | 50 | 138 | 104 | 172 | 66 | 148 | 2.5 |
| Strategy 7 | 147 | 22 | 281 | 47 | 177 | 137 | 204 | 66 | 183 | 5.2 |
| Strategy 8 | 177 | 22 | 335 | 61 | 177 | 137 | 204 | 66 | 183 | 5.2 |

*Initial CAPEX is defined as the CAPEX that occurs before first oil (within the first three years of development)

The simulation results are shown in terms of VARG curves in Figure 79 and summary of statistics in Table 32. The results are normalized to the ENPV of strategy 1. From the comparison of VARG curves and summary of statistics, we have the following observations:

- Four strategies without tieback flexibility: Strategies without tieback flexibility (e.g., strategies 1~4) have significantly lower expected NPV compared to strategies with tieback flexibility. The lower expected NPV is partially contributed by long negative tails in the VARG curves as shown in Figure 79. When the reserves in the core fields are smaller than the initial estimate, strategies without tieback flexibility cannot bring in new resources to make the project economically viable. ARM does not make much difference when tieback flexibility is disabled. Platform expansion flexibility, in fact, slightly reduces ENPV. This is partially due to the "false alarm" in the decision rule on capacity expansion while the underlying reserve for core field is not actually large enough to justify exercising the capacity expansion option. The difference between the true state vector $\vec{V}(t)$ and the estimate of this vector $\hat{\vec{V}}(t)$ may cause the "false alarm"[19]. For example, a reservoir may be tied back due to an overestimate of its reserve. These kinds of mistakes can be mitigated by developing more intelligent decision rules (e.g., introduce time delays and learning in the decision rule) but they cannot be completely eliminated due to the evolving uncertainty.

[19] "False alarm" here specifically refers to taking incorrect decisions (from a retrospective point of view) due to the estimation error of the state vector $\vec{V}(t)$.

- Four strategies with tieback flexibility: From the VARG curve, we can see that tieback flexibility significantly improves ENPV (e.g., increases ENPV by 32% from strategy 1 to 5) by reducing project downside risks. Tieback flexibility allows adding more resources (fluids to be processed) when the conditions for core fields turn out to be unfavorable. ARM flexibility demonstrates its value when tieback flexibility is enabled. For example, ARM flexibility increases ENPV by 20% from strategy 5 to 6. Capacity expansion flexibility further improves ENPV by extending the upside tail. However, there is a mixed effect between capacity expansion flexibility and ARM, the value of capacity expansion flexibility cannot be realized when ARM is disabled. For example, strategy 7 underperforms compared to strategy 6, although strategy 7 has capacity expansion flexibility. This shows that the value of these options is "nested" and does not add up linearly.
- Initial CAPEX: As shown in Table 32 tieback flexibility and capacity expansion flexibility do not increase a project's initial CAPEX significantly. However, this is based on the assumptions on cost of tieback flexibility (10% of the initial SURF cost) and cost of capacity expansion (0%, no cost). These assumptions need to be verified in detailed cost models in the future. Section 7.6 will illustrate a limited sensitivity study on the cost of flexibility.
- Total expected reserve and the number of tieback fields: Compared to strategy 1~4 (without tieback flexibility), strategies 5 and 6 (with tieback but no capacity expansion) increase the expected reserve by 48% and ties back 2.5 fields on average, and strategies 7 and 8 (with both tieback and capacity expansion) increase the expected reserve by 83% and ties back 5.2 fields on average. Therefore, the tieback and capacity expansion flexibility enables bringing in and processing more resources.

Table 33 and Table 34 show the statistics for tieback and capacity expansion flexibility. From Table 33, we can see that 3.5% of the runs with strategies 5 and 6 do not exercise tieback flexibility, but all runs with strategies 7 and 8 exercise tieback flexibility. Furthermore, the comparisons in Table 33 also show that capacity expansion flexibility increases the likelihood to tie back more fields. From Table 34, we can see the percentage of runs that exercise capacity expansion for strategies 3, 4, 7, and 8. Clearly, tieback flexibility significantly increases the possibility (or the need) for capacity expansion. This is because there is a need to increase capacity if more fields are tied back, and there is little chance (i.e., 5%) for the reserve (and production rates) of the core fields by themselves to trigger capacity expansion flexibility.

**Table 33:** Statistics for tieback flexibility

| | Strategies 5 or 6 (without capacity expansion flexibility) | Strategies 7 or 8 (with capacity expansion flexibility) |
|---|---|---|
| % of runs without exercising tieback | 3.50% | 0% |
| % of runs that exercise 1 tieback field | 14.00% | 0% |
| % of runs that exercise 2 tieback fields | 34.50% | 0.50% |
| % of runs that exercise 3 tieback fields | 28.50% | 1.50% |
| % of runs that exercise 4 tieback fields | 13.50% | 11.00% |
| % of runs that exercise 5 tieback fields | 5.50% | 54.50% |
| % of runs that exercise 6 tieback fields | 0.50% | 32.50% |

**Table 34:** Statistics for capacity expansion flexibility

| | Strategy 3 or 4 (without tieback flexibility) | Strategy 7 or 8 (with tieback flexibility) |
|---|---|---|
| % of runs that exercise capacity expansion flexibility | 0.50% | 93.00% |

We can apply the t-test to see whether the ENPV of any two strategies are statistically different from each other. Table 35 shows the pairwise t-test for the differences between ENPVs between any two strategies. The numbers shown in the table are the probabilities that any two distributions have the same mean (i.e., ENPV). If a 95% confidence interval is chosen, the t-test show that the differences among strategies 1~4 and the difference between strategies 6 and 7 are not statistically significant. Clearly, the difference between strategy 8 and the other 7 strategies are statistically significant and strategy 8 is the best among the eight strategies.

**Table 35:** Pairwise t-test for strategies 1~8

| Probability that two samples have the same mean | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| Strategy 1 | | 9.95E-01 | 4.45E-01 | 4.39E-01 | 1.26E-06 | 3.53E-15 | 5.47E-13 | 8.06E-26 |
| Strategy 2 | | | 4.49E-01 | 4.42E-01 | 1.20E-06 | 3.26E-15 | 5.08E-13 | 7.30E-26 |
| Strategy 3 | | | | 9.92E-01 | 3.06E-08 | 3.55E-17 | 5.90E-15 | 8.04E-28 |
| Strategy 4 | | | | | 2.79E-08 | 3.05E-17 | 5.11E-15 | 6.65E-28 |
| Strategy 5 | | | | | | 1.21E-04 | 3.95E-03 | 5.51E-14 |
| Strategy 6 | | | | | | | 2.53E-01 | 1.24E-05 |
| Strategy 7 | | | | | | | | 5.11E-08 |
| Strategy 8 | | | | | | | | |

Given the full factorial DOE results, we can estimate the "main" effects of the three levels of flexibility. A regression model can be obtained by DOE analysis:

$$ENPV(x_1, \quad x_2, \quad x_3) = 124.5 + 27.5x_1 + 3.5x_2 + 6.25x_3 + 6.5x_1x_2 + 6.25x_1x_3 + 1.25x_2x_3 \text{ [Eq. 7 - 2]}^{20}$$

where $x_1$ : tieback flexibility, it takes value -1 (no tieback flexibility) or 1 (with tieback flexibility); $x_2$: capacity expansion flexibility; $x_3$: ARM flexibility. Because the interaction terms are considered, the absolute values of the coefficients in Equation 7-2 do not represent the net effects of flexibilities. If $x_1 \sim x_3$ all take values of -1, the results represent the baseline ENPV without any flexibility. Equation 7-2 provides a formal way to define the *Value of Flexibility (VOF)*. For example, the value of tieback flexibility (strategy level flexibility) is defined as the main effect $x_1$:

$$\frac{1}{4}\begin{pmatrix} ENPV(+1,-1,-1) + ENPV(+1,-1,+1) + ENPV(+1,+1,-1) + ENPV(+1,+1,+1) \\ - ENPV(-1,-1,-1) - ENPV(-1,-1,+1) - ENPV(-1,+1,-1) - ENPV(-1,+1,+1) \end{pmatrix} = 55$$

The value of tieback flexibility is the average of the differences between the strategies with tieback flexibility and the strategies without tieback flexibility. Similarly, we can obtain other main effects and interaction effects. Table 36 shows the main effects and interaction effects.

[20] This equation is normalized based on the ENPV of strategy 1.

**Table 36:** Main effects and interaction effects on ENPV (with initial 150 MBD capacity)

| | $x_1$ (value of tieback flexibility) | $x_2$ (value of capacity flexibility) | $x_3$ (value of ARM Flexibility) | $x_1x_2$ | $x_1x_3$ | $x_2x_3$ |
|---|---|---|---|---|---|---|
| Main effects or interaction effects (%) | 55 | 7 | 12.5 | 13 | 12.5 | 2.5 |

With the results of main effects and interaction effects, we can plot a Pareto chart to show the relative contribution of each type of flexibility (and their interactions) to a project's ENPV. Figure 80 shows the Pareto chart for the three main effects and three second order interaction effects. The main effects represent the incremental value of flexibility to a project's ENPV. Clearly, tieback flexibility contributes most (55% improvement) to the ENPV. The second largest main effect is operational flexibility. In this case study, capacity flexibility has less impact than operational flexibility. The interaction effects with tieback flexibility (*i.e.*, $x_1x_2$, $x_1x_3$) have stronger impact on ENPV than the interaction effect (*i.e.*, $x_2x_3$) between capacity and operational flexibility. The overall approach illustrated in this chapter provides a formal way to quantify the Value of Flexibility (VOF) under uncertainty by attributing incremental contributions to individual sources of flexibilities.

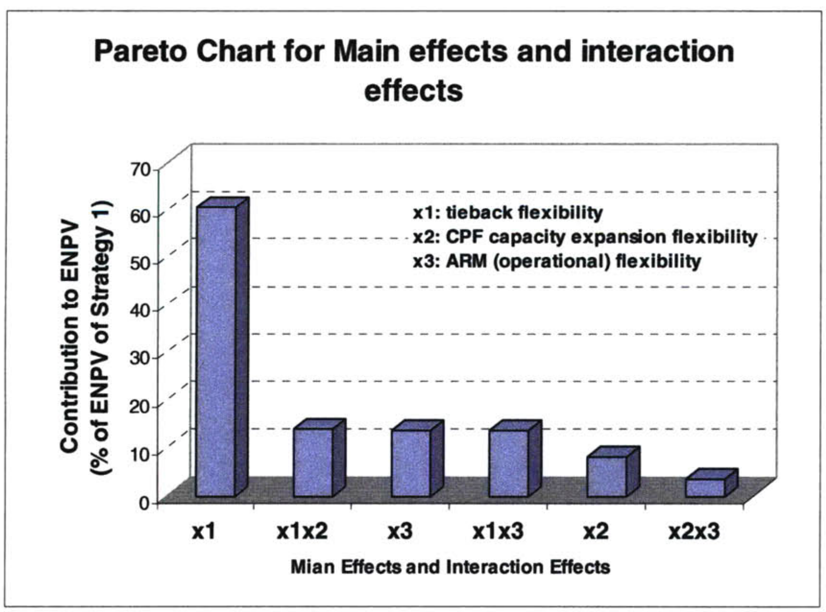


**Figure 80:** Pareto chart of the main effects and interaction effects (with initial 150 MBD capacity)

**(2) Development strategies with 175 MBD capacity**

The second set of strategies is based on the initial CPF with 175 MBD capacity. It assumes that there is no platform expansion flexibility since the platform is bigger than what would be required (150 MBD) from year 0. A full factorial design of experiments is outlined in Table 37. There are two types of flexibility; therefore there are four strategies ($2^2$=4) for the full factorial DOE.

**Table 37:** Design of experiments for strategies 9~12 (with 175 MBD initial capacity)

| | Strategic flexibility | Tactical flexibility | Operational flexibility |
|---|---|---|---|
| Factors for flexibility | Tieback flexibility (Y/N) | No platform capacity expansion flexibility (N) | Active reservoir management (Y/N) |
| Strategy 9 | N | N | N |
| Strategy 10 | N | N | Y |
| Strategy 11 | Y | N | N |
| Strategy 12 | Y | N | Y |

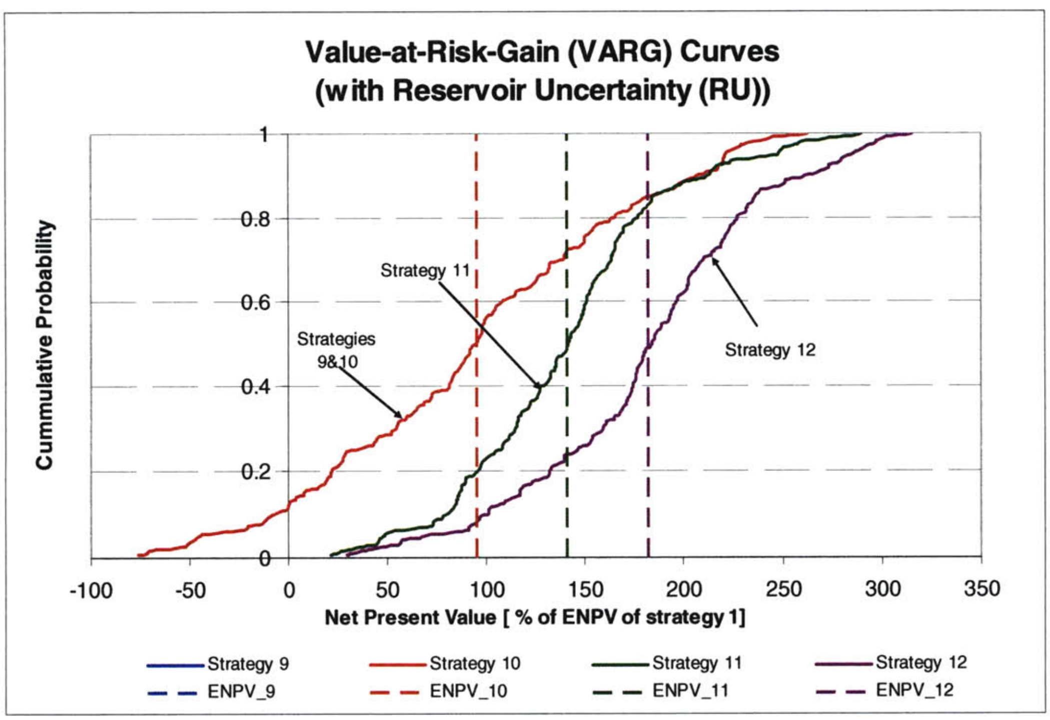


**Figure 81:** VARG curves for strategies 9~12 under RU

**Table 38:** Summary of statistics for strategies 9~12 under RU

| | NPV (% of ENPV for strategy 1 ) | | | | CAPEX (% of expected CAPEX for strategy 1) | | | | Expected total reserve | Expected # of tiebacks |
|---|---|---|---|---|---|---|---|---|---|---|
| | Expected | Min | Max | σ(NPV) | Expected | Min | Max | Initial* | | |
| Strategy 1 | 100 | -66 | 251 | 74 | 100 | 100 | 100 | 64 | 100 | 0.0 |
| Strategy 2 | 100 | -66 | 255 | 74 | 100 | 100 | 100 | 64 | 100 | 0.0 |
| Strategy 3 | 94 | -88 | 262 | 77 | 102 | 100 | 109 | 64 | 100 | 0.0 |
| Strategy 4 | 94 | -88 | 260 | 77 | 102 | 100 | 109 | 64 | 100 | 0.0 |
| Strategy 5 | 132 | 7 | 266 | 54 | 138 | 104 | 172 | 66 | 148 | 2.5 |
| Strategy 6 | 152 | 27 | 276 | 50 | 138 | 104 | 172 | 66 | 148 | 2.5 |
| Strategy 7 | 147 | 22 | 281 | 47 | 177 | 137 | 204 | 66 | 183 | 5.2 |
| Strategy 8 | 177 | 22 | 335 | 61 | 177 | 137 | 204 | 66 | 183 | 5.2 |
| Strategy 9 | 95 | -76 | 262 | 78 | 103 | 103 | 103 | 67 | 100 | 0.0 |
| Strategy 10 | 95 | -76 | 262 | 78 | 103 | 103 | 103 | 67 | 100 | 0.0 |
| Strategy 11 | 141 | 21 | 290 | 53 | 165 | 130 | 191 | 69 | 177 | 4.6 |
| Strategy 12 | 182 | 30 | 315 | 60 | 165 | 130 | 191 | 69 | 177 | 4.6 |

The simulation results are shown in Figure 81 and Table 38. From the comparison of VARG curves and summary of statistics, we have the following observations:

- Tieback flexibility: Strategies (11~12) with tieback flexibility outperform the strategies (9~10) without tieback flexibility. For example, enabling tieback flexibility in strategy 11 improves the ENPV from 95% (strategy 9 or 10) to 141%. This improvement is achieved by cutting the downside tail in the VARG curve because the tieback flexibility allows to bring in more resources when the reserves in the core fields turns out to be unfavorable.
- ARM flexibility: ARM flexibility further improves ENPV when tieback flexibility is enabled. Comparing strategy 12 to 11, ARM flexibility improves ENPV from 141% to 182%. However, when tieback flexibility is disabled, ARM flexibility does not change ENPV at all because there are no additional fluids to operate on.
- 175MBD vs. 150 MBD: Compared to most flexibility cases between these two designs, strategy 12 slightly outperforms strategy 8 in terms of ENPV, min NPV and σ(NPV). However, the max NPV for strategy 12 is less than strategy 8 because strategy 12 cannot achieve higher upside gain due to its 175 MBD capacity limit, while strategy 8 can expand platform capacity up to 200 MBD. This points out that there is room for improvement in both the initial configuration as well as the decision rules for exercising flexibility.

Table 39 shows the pairwise t-test for the ENPV of strategies 9 ~12. From this t-test, we can see that except for the pair of strategies 9 and 10, the differences of ENPVs for the rest pairs of strategies are statistically significant. Therefore, statically we can conclude that: $ENPV_{12} > ENPV_{11} > ENPV_{9/10}$.

**Table 39:** Pairwise t-test for strategies 9~12

| Probability that two samples have the same mean | Strategy 9 | Strategy 10 | Strategy 11 | Strategy 12 |
|---|---|---|---|---|
| Strategy 9 | | 1.00E+00 | 2.31E-11 | 1.58E-30 |
| Strategy 10 | | | 2.31E-11 | 1.57E-30 |
| Strategy 11 | | | | 1.17E-12 |
| Strategy 12 | | | | |

Table 40 shows the t-test for between two strategy groups (strategies 1~8 and strategies 9~12). The differences of ENPV for the following pairs are not statistically significant (with 95% confidence interval):

- Strategies 1~4 and strategies 9~10
- Strategies 5 and 11, strategies 7 and 11
- Strategy 8 and 12

**Table 40:** T-test between strategies 1~8 and strategies 9~12

| Probability that two samples have the same mean | Strategy 9 | Strategy 10 | Strategy 11 | Strategy 12 |
|---|---|---|---|---|
| Strategy 1 | 0.5361 | 0.5359 | 4.909E-10 | 2.453E-29 |
| Strategy 2 | 0.5401 | 0.5399 | 4.620E-10 | 2.201E-29 |
| Strategy 3 | 0.8883 | 0.8885 | 7.125E-12 | 2.693E-31 |
| Strategy 4 | 0.8804 | 0.8806 | 6.334E-12 | 2.190E-31 |
| Strategy 5 | 7.972E-08 | 7.949E-08 | 0.0854 | 2.258E-17 |
| Strategy 6 | 1.492E-16 | 1.485E-16 | 3.224E-02 | 7.424E-08 |
| Strategy 7 | 2.308E-14 | 2.298E-14 | 0.2725 | 9.003E-11 |
| Strategy 8 | 4.259E-27 | 4.233E-27 | 9.038E-10 | 0.3743 |

Similar to the procedure shown in the previous section, we can use DOE analysis to obtain a regression model for ENPV and to estimate the main effects and interaction effects. Equation 7-3 shows the regression model and Table 41 shows the main effects and interaction effects. A

Pareto chart based on the result of regression analysis is shown in Figure 82. Obviously, tieback flexibility has the highest impact on ENPV.

$$ENPV(x_1 \quad x_2) = 128.25 + 33.25x_1 + 10.25x_3 + 10.25x_1x_3 \qquad \text{[Eq. 7 - 3]}^{21}$$

**Table 41:** Main effects and interaction effects on ENPV (with initial 175 MBD capacity)

| | $x_1$ (value of tieback flexibility) | $x_3$ (value of ARM flexibility) | $x_1x_3$ |
|---|---|---|---|
| Main effects or interaction effects | 66.5 | 20.5 | 20.5 |

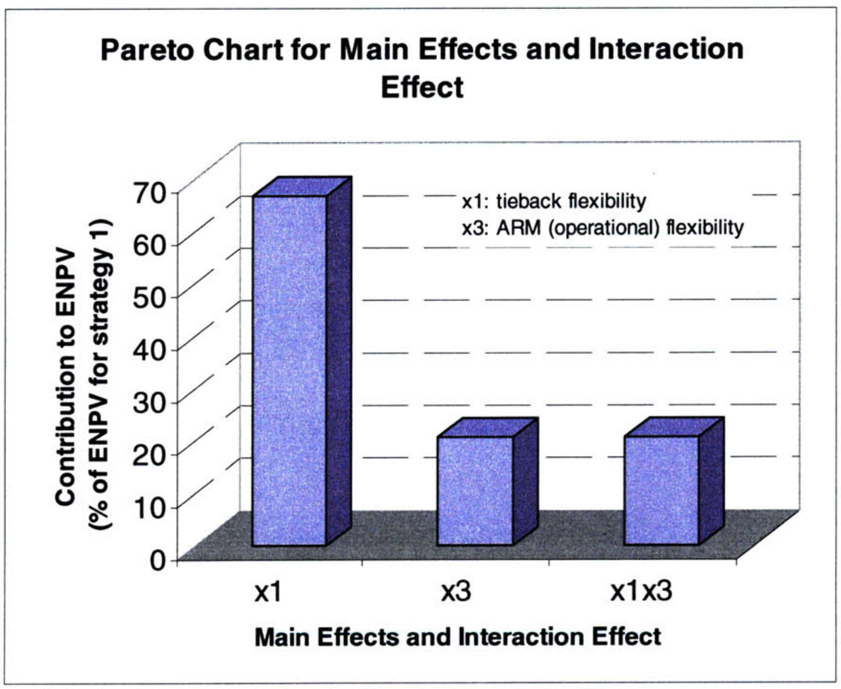


**Figure 82:** Pareto chart of the main effects and interaction effects (with initial 175 MBD capacity)

[21] This equation is normalized based on the ENPV of strategy 1.

**Summary of Section 7.5.1**

As illustrated in this section, the VARG curves provide a holistic view of a strategy's probabilistic outcomes. To compare different strategies, we should not only look at ENPV but also at the distribution of NPV. Two strategies with the same ENPVs might have quite different distributions. Risk adverse decision makers would generally prefer the strategy with shorter downside tail. Figure 83 shows the ENPV vs. σ(NPV) for the 12 strategies. This plot looks similar to a variance-return plot in financial portfolio theory. We may prefer solutions which skew to the upside rather than minimal variance.

Three strategy clusters can be identified from this plot:

- Cluster 1: The first cluster includes "high risk and low return" strategies (i.e., strategies 1, 2, 3, 4, 9, and 10). These strategies correspond to strategies without tieback flexibility. Therefore, development strategies without tieback flexibility will expose a project to high risk and result in potentially low return.
- Cluster 2: The second cluster includes "low risk and mid-range return" strategies (i.e., strategies 5, 6, 7 and 11). These strategies enable tieback flexibility so that subsurface uncertainty is mitigated and the project's ENPV is improved. However, either ARM or capacity expansion flexibility is not enabled.
- Cluster 3: The third cluster includes "mid-range risk and high return" strategies (i.e., 8, 12). The strategies can be seen as the "the best strategies" as multiple levels of flexibility are combined in such ways that ENPV is maximized with a slight increase of the standard deviation of NPV. Moreover, the increase of variance is not necessarily a bad thing as the VARG curves are extended towards the upside direction. Strategies 8 (full flexibility with 150 MBD initial capacity) and 12 (tieback and ARM flexibility with 175 MBD initial capacity) are the best strategies among the 12 alternatives. However, they are also potentially the most complex strategies to implemented in practice.

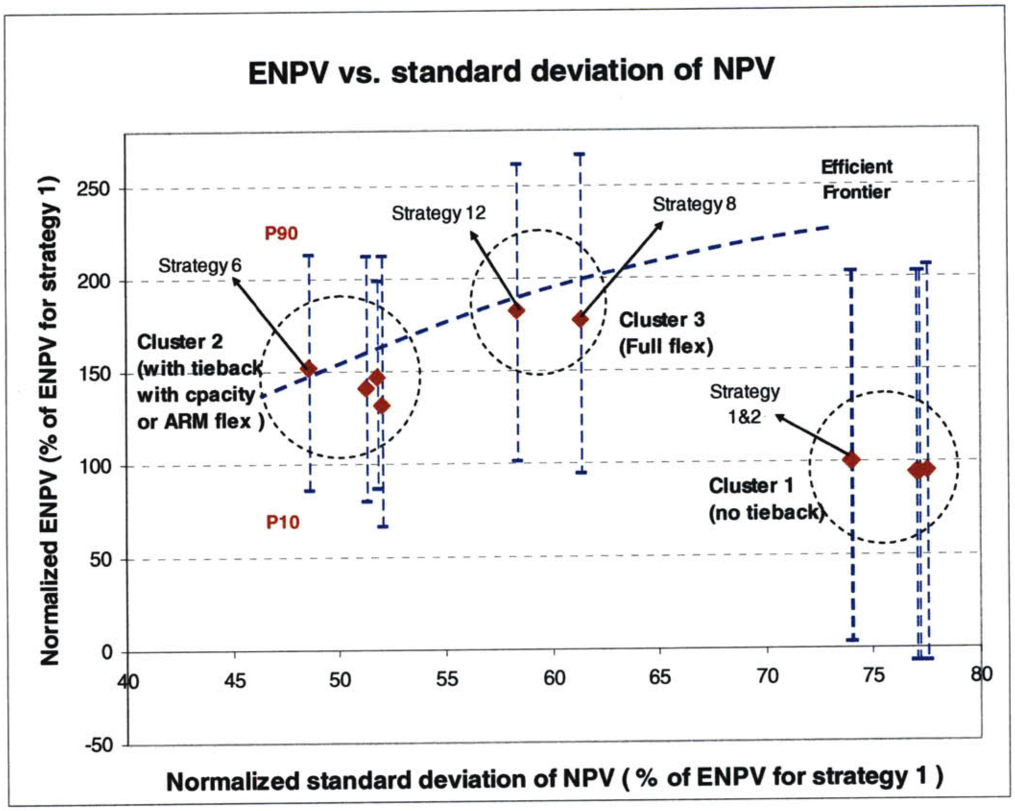


**Figure 83:** ENPV vs. $\sigma$(NPV) plot for the 12 strategies

The dashed curve shown in Figure 83 represents the "efficient front" for field development strategies. In financial portfolio theory, it said that no portfolio (strategies) can perform better than the strategies on the efficient front given the risk and return tradeoff[22]. In Figure 83, each strategy has a bar (between P10 and P90) showing the spread of NPV. It appears that the distribution is symmetric with respect to ENPV. Other ways of representing the information is to plot "gain-return" and "risk-return" curves. Figure 84 and Figure 85 show the ENPV vs. P90 (upside gain) or P10 (downside risk) of NPV respectively. We can clearly identify the three strategy clusters. In the gain-return plot, cluster 3 with full flexibility improves the upside gain from 200% to 260%. In the risk-return plot, strategy cluster 3 reduces the downside risk and improves P10 from ~ -10% to 100%. In summary, the three levels of flexibility improve the ENPV by reducing downside risk and increasing upside gain.

[22] Copeland, T. E., Weston, J. F. and Shastri, K. (2004) "Financial Theory and Corporate Policy", 4th ed., Addison Wesley.

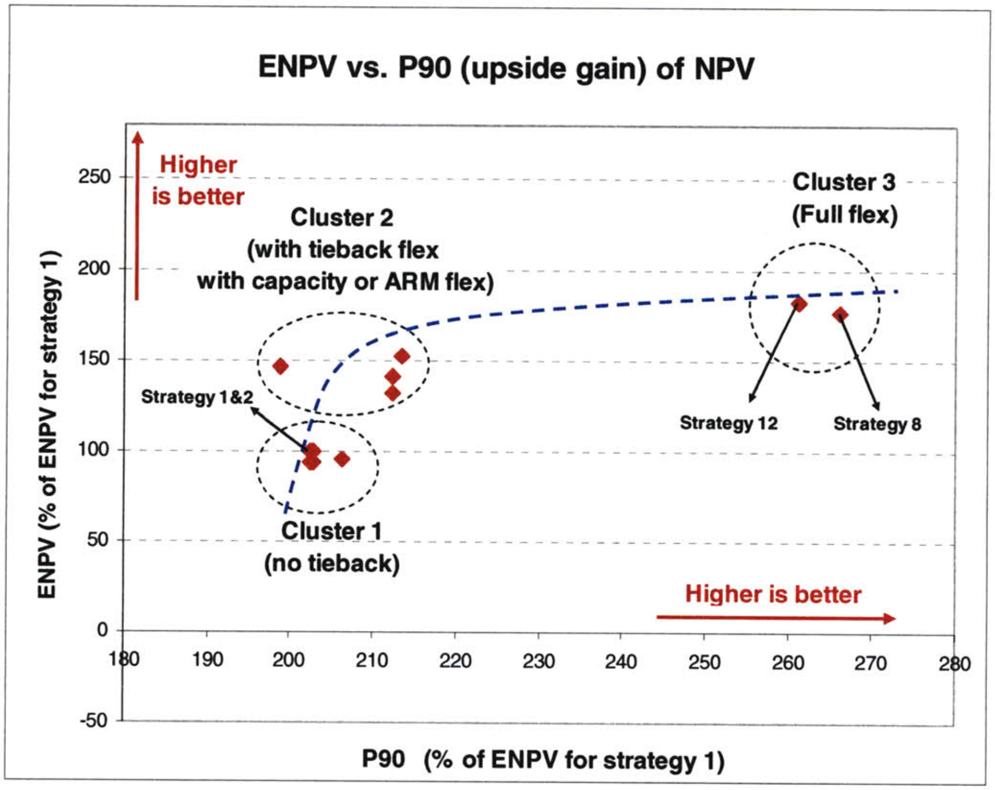


**Figure 84:** ENPV vs. P90 (upside gain) plot for the 12 strategies

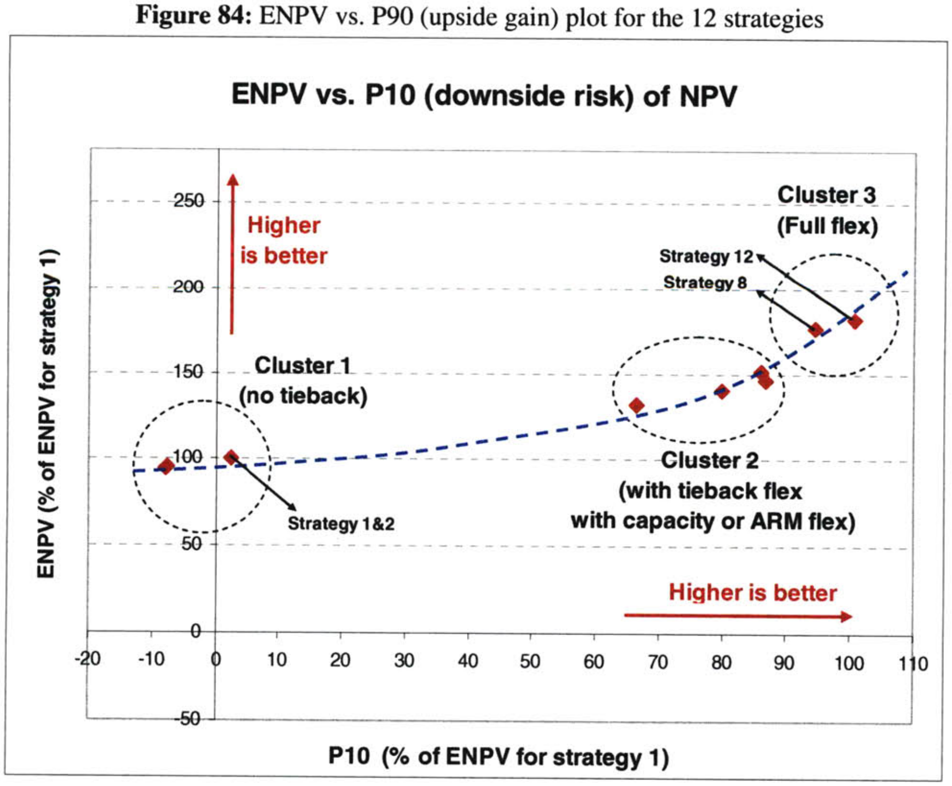


**Figure 85:** ENPV vs. P10 (downside risk) plot for the 12 strategies

## 7.5.2 Simulations with RU + FU

In this section, we simulate the same 12 strategies under both reservoir and facility uncertainty. The simulation setups for these 12 strategies are the same as Section 7.5.1. The decision rules for tieback and capacity expansion flexibility still remain the same. Figure 86 and Figure 87 shows the VARG curves for strategies 1~8 and 9~12 respectively. Table 42 gives the summary of the statistics for these 12 strategies. In order to remain consistent, all NPV related metrics are normalized against the ENPV and all CAPEX related metrics are normalized against the expected CAPEX of the strategy 1 with RU only. From these figures and summary of statistics, we can see that facility uncertainty reduces the NPVs for all 12 strategies (on average 8% reduction) but it does not change the rank order of theses strategies. This can be explained by the reduced expected facility availability by introducing facility uncertainty. The shapes of VARG curves remain similar to VARG curves with reservoir uncertainty only.

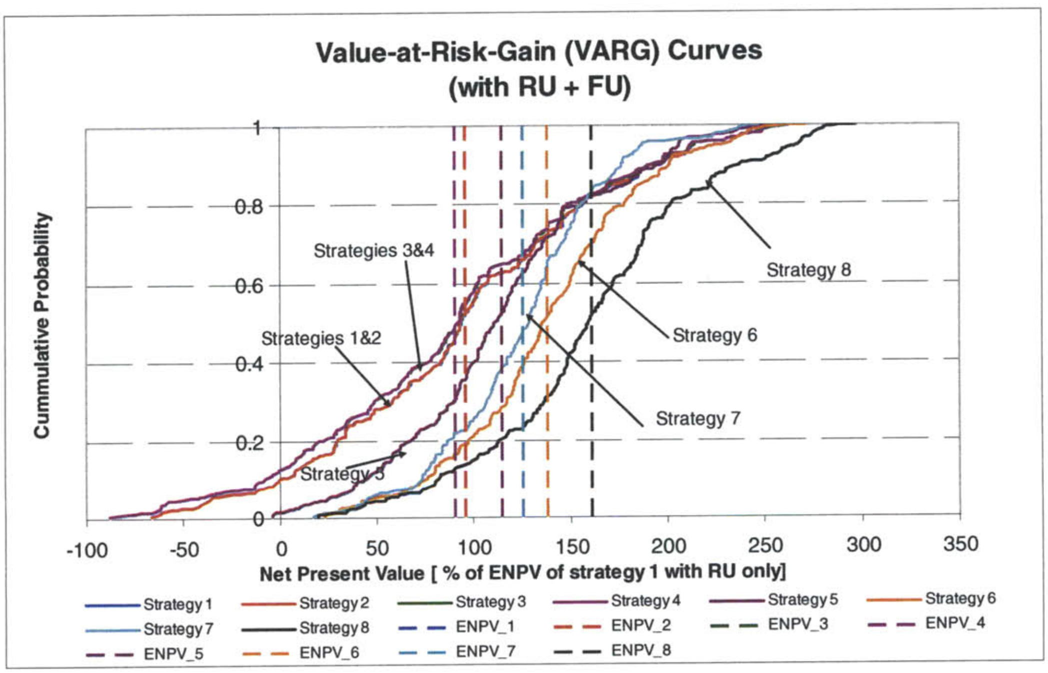


**Figure 86:** VARG Curves for Strategies 1~8 (with Initial 150 MBD Capacity) under RU + FU

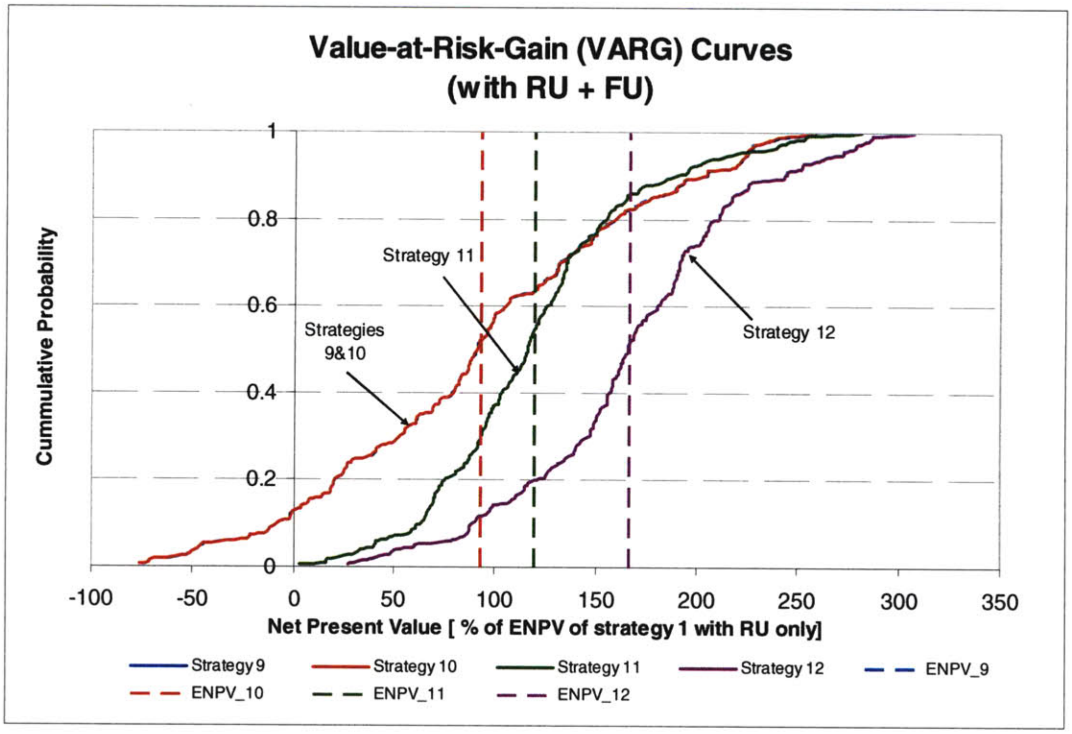


**Figure 87:** VARG Curves for Strategies 9~12 (with Initial 175 MBD Capacity) under RU + FU

**Table 42:** Summary of Statistics for Strategies 1~ 12 under RU + FU

| | NPV (% of ENPV for strategy 1 with RU only ) | | | | CAPEX (% of expected CAPEX for strategy 1 with RU only) | | | | Expected total reserve | Expected # of tiebacks |
|---|---|---|---|---|---|---|---|---|---|---|
| | Expected | Min | Max | σ(NPV) | Expected | Min | Max | Initial* | | |
| Strategy 1 | 96 | -66 | 269 | 73 | 100 | 100 | 100 | 64 | 100 | 0.0 |
| Strategy 2 | 96 | -66 | 268 | 72 | 100 | 100 | 100 | 64 | 100 | 0.0 |
| Strategy 3 | 90 | -88 | 265 | 76 | 102 | 100 | 109 | 64 | 100 | 0.0 |
| Strategy 4 | 90 | -88 | 265 | 76 | 102 | 100 | 109 | 64 | 100 | 0.0 |
| Strategy 5 | 114 | -4 | 265 | 54 | 138 | 104 | 172 | 66 | 148 | 2.5 |
| Strategy 6 | 138 | 23 | 271 | 49 | 138 | 104 | 172 | 66 | 148 | 2.5 |
| Strategy 7 | 125 | 17 | 247 | 43 | 177 | 137 | 204 | 66 | 183 | 5.2 |
| Strategy 8 | 161 | 19 | 297 | 58 | 177 | 137 | 204 | 66 | 183 | 5.2 |
| Strategy 9 | 93 | -76 | 258 | 77 | 103 | 103 | 103 | 67 | 100 | 0.0 |
| Strategy 10 | 93 | -76 | 258 | 77 | 103 | 103 | 103 | 67 | 100 | 0.0 |
| Strategy 11 | 120 | 3 | 281 | 51 | 165 | 130 | 191 | 69 | 176 | 4.6 |
| Strategy 12 | 167 | 27 | 307 | 56 | 165 | 130 | 191 | 69 | 176 | 4.6 |

### 7.5.3 Simulations with RU + FU + MU

In this section, we turn on all three types of uncertainty – reservoir, facility, and market uncertainties. Market Uncertainty (MU) specifically refers to the uncertainty in crude oil prices. The formulations for these 12 strategies are the same as the strategies in Sections 7.5.1 and 7.5.2 except the following two aspects:

- Initial configuration: the initial configuration for strategies with tieback flexibility (strategies 5~8 and 11~12) starts from two core fields but the initial configuration for strategies without tieback flexibility starts from four core fields. In Section 7.5.1 and 7.5.2, all strategies start from four core fields. Under the market uncertainty, a smaller initial configuration allows the flexible strategies to better respond (without exercising tieback options) to downside risk in market uncertainty.
- Decision rules: The decision rules flexibility strategy is based on the estimate of state vector $\hat{\vec{V}}(t)$. Now, in addition to reserve estimate, the market uncertainty is also taken into account in the state vector $\hat{\vec{V}}(t)$. The decision rule sets up a minimal crude oil price (i.e., \$25/barrel) as a threshold for exercising tieback or capacity expansion flexibility. A moving average of crude oil price is used as a decision variable in $\hat{\vec{V}}(t)$. In order to exercise tieback or capacity expansion flexibility, all conditions based on the state vector $\hat{\vec{V}}(t)$ (i.e., reserve estimate, platform capacity, crude oil price) have to be satisfied simultaneously.

Figure 88 and Figure 89 show the VARG curves for strategies 1~8 and 9~12 respectively. Table 43 gives the summary of the statistics for the 12 strategies. Again, the results are all normalized against the ENPV or expected CAPEX of strategy 1 with RU only. By introducing market uncertainty, the distribution of NPV becomes wider and the downside and upside tails of different strategies appear to merge together. This is because the market uncertainty becomes the dominant uncertain factor and dilutes the differences among different strategies. However, the results preserve the rank order for the 12 strategies. Flexibility brings in value as follows:

- From an ENPV point of view, the most flexible strategies (i.e., strategy 8 and 12) improve ENPV from 146% (baseline strategy 1) to 257% and 251% respectively.

- From a min NPV point of view, the most flexible strategies (i.e., strategy 8 and 12) reduce downside risk and increase min NPV from -99% (baseline strategy 1) to -71% and -70% respectively.
- From a max NPV point of view, the most flexible strategies (i.e., strategy 8 and 12) capture upside gains and increase max NPV from 400% (baseline strategy 1) to 578% and 559% respectively.
- From an initial CAPEX point of view, the most flexible strategies (i.e., strategy 8 and 12) reduce the initial CAPEX from 64% (baseline strategy 1) to 58% and 61% respectively. Thus, flexibility reduces the initial CAPEX risk.

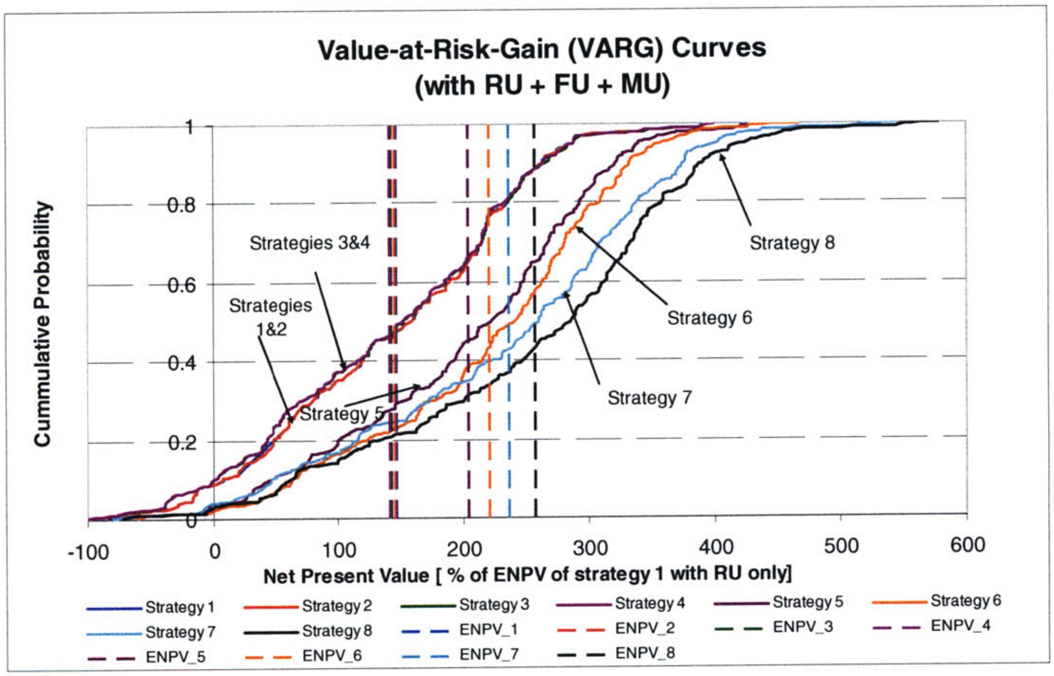


**Figure 88:** VARG curves for strategies 1~8 (with initial 150 MBD capacity) under RU + FU + MU

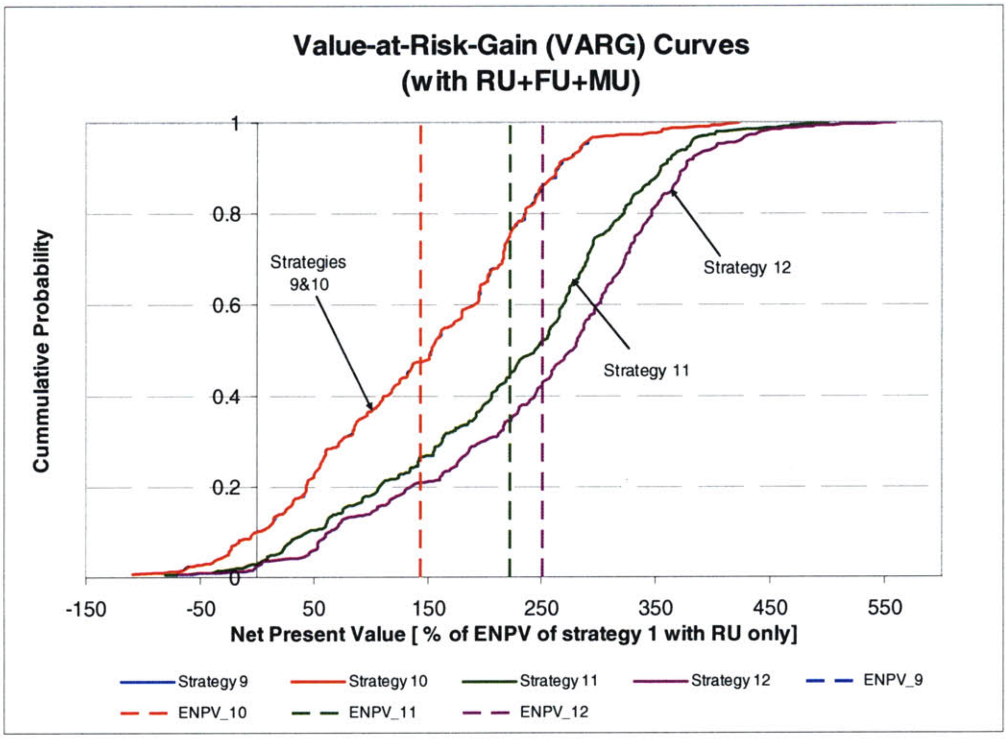


**Figure 89:** VARG curves for strategies 9~12 (with initial 175 MBD capacity) under RU + FU + MU

**Table 43:** Summary of statistics for strategies 1~ 12 under RU + FU + MU

| | NPV (% of ENPV for strategy 1 with RU only ) | | | | CAPEX (% of expected CAPEX for strategy 1 with RU only) | | | | Expected total reserve | Expected # of tiebacks |
|---|---|---|---|---|---|---|---|---|---|---|
| | Expected | Min | Max | σ(NPV) | Expected | Min | Max | Initial* | | |
| Strategy 1 | 146 | -99 | 400 | 100 | 100 | 100 | 100 | 64 | 100 | 0.0 |
| Strategy 2 | 146 | -99 | 400 | 100 | 100 | 100 | 100 | 64 | 100 | 0.0 |
| Strategy 3 | 142 | -99 | 400 | 104 | 102 | 100 | 109 | 64 | 100 | 0.0 |
| Strategy 4 | 142 | -99 | 399 | 103 | 102 | 100 | 109 | 64 | 100 | 0.0 |
| Strategy 5 | 204 | -83 | 463 | 104 | 131 | 93 | 161 | 58 | 146 | 3.8 |
| Strategy 6 | 221 | -60 | 468 | 102 | 131 | 93 | 161 | 58 | 146 | 3.8 |
| Strategy 7 | 236 | -81 | 544 | 123 | 167 | 115 | 193 | 58 | 178 | 6.3 |
| Strategy 8 | 257 | -71 | 578 | 125 | 167 | 115 | 193 | 58 | 178 | 6.3 |
| Strategy 9 | 144 | -109 | 422 | 104 | 103 | 103 | 103 | 67 | 100 | 0 |
| Strategy 10 | 144 | -109 | 422 | 104 | 103 | 103 | 103 | 67 | 100 | 0 |
| Strategy 11 | 222 | -81 | 500 | 115 | 155 | 109 | 185 | 61 | 171 | 6 |
| Strategy 12 | 251 | -70 | 559 | 117 | 155 | 109 | 185 | 61 | 171 | 6 |

## *7.6 Sensitivity Analysis*

The simulation results shown in Section 7.5 depend on assumptions and parameters in the screening models, the uncertainty models, and the specific decision rules. A complete and in-depth sensitivity study for all strategies on all parameters in the models and decision rules goes beyond the scope of this thesis. Similar to Section 6.5, we select several key parameters and conduct both global and local analyses for the strategies 5 and 8 under reservoir uncertainty only. In this section, the following three parameters are selected for sensitivity analysis.

- *The cost of tieback flexibility*: For tieback flexibility, we assume the cost of the tieback option is $x\%$ ($x$ ~ 0%~50%) of the initial SURF cost. The nominal value for this parameter is 10%.
- *The cost of capacity expansion flexibility*: For platform capacity expansion flexibility, we assume the cost of this option is $y\%$ ($y$ ~ 0%~70%) of the initial platform cost. The nominal value for this parameter is 0%, in other words, this flexibility comes "free".
- *The timing of enabling (tieback and capacity expansion) flexibility*: this is a parameter in the decision rule, where we assume that the decision rule allows to exercise tieback or capacity flexibility at the year $n_a$. The nominal value for this parameter is 4.

### 7.6.1 Global Sensitivity Analysis

**(a) Global sensitivity to the cost of tieback flexibility**

We vary the cost of tieback flexibility from 0% up to 50% while keeping the other two parameters (cost of capacity expansion and timing of enabling flexibility) at their nominal values. The purpose is to identify the conditions at which the strategies with tieback flexibility (e.g., strategy 5 and 8) become inferior to the baseline inflexible strategy (e.g., strategy 1). At these conditions, the rank order of different strategies starts to crossover. These sensitivity analyses will give "confidence intervals" to decision makers for comparing and choosing the strategies.

The cost of tieback flexibility is expressed as a percentage of the initial SURF cost of strategy 1. Table 44 and Table 45 show the results of sensitivity analysis for strategies 5 and 8. From these two tables, we can see that the ENPV of strategy 5 becomes less than the strategy 1 when the cost of tieback flexibility increases up to 30% of the initial SURF cost, and the ENPV of strategy

8 becomes less than strategy 1 when cost of tieback flexibility increases up to 50%. Strategy 8 can hold its rank order at higher cost of tieback flexibility because it enables all three levels of flexibility while strategy 5 has only tieback flexibility.

**Table 44:** Global sensitivity on the cost of tieback flexibility (strategy 5, RU only)

| | **Strategy 5** (% of ENPV or Expected CAPEX of strategy 1) | | | | | **Strategy 1** |
|---|---|---|---|---|---|---|
| **Cost of tieback flexibility (% of the initial SURF cost of strategy 1)** | 0% | 5% | **10%** | 20% | 30% | |
| **Cost of tieback flexibility (% of the total CAPEX of strategy 1)** | 0.0% | 2.0% | **4.1%** | 8.1% | 12.2% | |
| **ENPV** | 149 | 140 | **132** | 115 | 97 | 100 |
| **Min NPV** | 28 | 18 | **7** | -14 | -36 | -66 |
| **Max NPV** | 258 | 256 | **266** | 278 | 267 | 251 |
| **Expected CAPEX** | 133 | 136 | **138** | 144 | 150 | 100 |
| **Initial CAPEX** | 64 | 65 | **66** | 69 | 71 | 64 |

**Table 45:** Global sensitivity on the cost of tieback flexibility (strategy 8, RU only)

| | **Strategy 8** (% of ENPV or Expected CAPEX of strategy 1) | | | | | | | **Strategy 1** |
|---|---|---|---|---|---|---|---|---|
| **Cost of tieback flexibility (% of the initial SURF cost of strategy 1)** | 0% | 5% | **10%** | 20% | 30% | 40% | 50% | |
| **Cost of tieback flexibility (% of the total CAPEX of strategy 1)** | 0.0% | 2.0% | **4.1%** | 8.1% | 12.2% | 16.3% | 20.4% | |
| **ENPV** | 198 | 188 | **177** | 155 | 134 | 112 | 91 | 100 |
| **Min NPV** | 43 | 33 | **22** | 2 | -19 | -40 | -61 | -66 |
| **Max NPV** | 328 | 327 | **335** | 315 | 295 | 274 | 253 | 251 |
| **Expected CAPEX** | 169 | 173 | **177** | 185 | 192 | 200 | 207 | 100 |
| **Initial CAPEX** | 64 | 65 | **66** | 69 | 71 | 74 | 76 | 64 |

### (b) Global sensitivity to the cost of capacity expansion flexibility

Similar to the previous sensitivity analysis, we vary the cost of capacity expansion flexibility from 0% up to 70% while keep the other two parameters (cost of tieback flexibility and timing of enabling flexibility) at their nominal values. Table 46 and Table 47 show the results of sensitivity analysis for strategies 5 and 8. The ENPVs of strategies 5 and 8 start to become less than the ENPV of strategy 1 when the cost of capacity flexibility increases up to 40% and 70% respectively.

**Table 46:** Global sensitivity on the cost of capacity expansion flexibility (strategy 5, RU only)

| | **Strategy 5** (% of ENPV or Expected CAPEX of strategy 1) | | | | | | **Strategy 1** |
|---|---|---|---|---|---|---|---|
| **Cost of capacity flexibility (% of the platform cost of Strategy 1)** | **0%** | 5% | 10% | 20% | 30% | 40% | |
| **Cost of capacity flexibility (% of the total CAPEX of Strategy 1)** | **0.0%** | 1.3% | 2.6% | 5.2% | 7.8% | 10.5% | |
| **ENPV** | **132** | 127 | 123 | 114 | 105 | 96 | 100 |
| **Min NPV** | **7** | 2 | -2 | -11 | -20 | -29 | -66 |
| **Max NPV** | **366** | 271 | 282 | 274 | 266 | 258 | 251 |
| **Expected CAPEX** | **138** | 140 | 141 | 144 | 146 | 149 | 100 |
| **Initial CAPEX** | **66** | 68 | 69 | 72 | 74 | 77 | 64 |

**Table 47:** Global sensitivity on the cost of capacity expansion flexibility (strategy 8, RU only)

| | **Strategy 8** (% of ENPV or Expected CAPEX of strategy 1) | | | | | | | **Strategy 1** |
|---|---|---|---|---|---|---|---|---|
| **Cost of capacity flexibility (% of the platform cost of Strategy 1)** | **0%** | 5% | 10% | 20% | 30% | 50% | 70% | |
| **Cost of capacity flexibility (% of the total CAPEX of Strategy 1)** | **0.0%** | 1.3% | 2.6% | 5.2% | 7.8% | 13.1% | 18.3% | |
| **ENPV** | **177** | 171 | 166 | 155 | 144 | 121 | 99 | 100 |
| **Min NPV** | **22** | 17 | 11 | 0 | -11 | -34 | -57 | -66 |
| **Max NPV** | **335** | 330 | 324 | 314 | 303 | 280 | 257 | 251 |
| **Expected CAPEX** | **177** | 179 | 180 | 184 | 187 | 194 | 201 | 100 |
| **Initial CAPEX** | **66** | 68 | 69 | 72 | 74 | 79 | 85 | 64 |

### (c) Global sensitivity to the timing of enabling flexibility

Table 48 and Table 49 show the results of sensitivity analysis to the timing of enabling flexibility. As we postpone the timing of enabling flexibility ($n_a$) from year 2 to year 9, the ENPV increases to a maximal value at year 5 and then decreases. Figure 90 shows the overall trend for ENPV vs. $n_a$ .There are several reasons for this phenomenon:

- As the timing for enabling flexibility is delayed (increased $n_a$), the volatility of reserve estimates decreases and potentially the decision rule can make better decisions as information becomes more accurate.

- However, due to the time value of money, NPV may be penalized by delayed timing of enabling flexibility (such as opportunity of tieback and capacity expansion).
- Furthermore, the decision rule only allows to exercise one tieback field at each time step and the last year of enabling flexibility ($n_b$) is set as year 10. The time window for enabling tieback or capacity expansion flexibility is [$n_a$ $n_b$]. Therefore, a delayed starting year of enabling flexibility will decrease the total number of fields can be tied back. For example, the expected number of tieback fields drops to two when $n_a$ increases to 9 for strategy 8. Future work should consider the option of tying back more than one field at once.

Therefore, the competing forces among these three aspects drive the behavior shown in Figure 90. The optimal timing of first enabling the exercising of flexibility appears to be year 5 for this particular case.

**Table 48:** Global sensitivity on the timing of enabling flexibility (strategy 5, RU only)

| | **Strategy 5** (% of ENPV or Expected CAPEX of strategy 1) | | | | | | | | **Strategy 1** |
|---|---|---|---|---|---|---|---|---|---|
| **Timing of enabling flexibility (Years)** | 2 | 3 | **4** | 5 | 6 | 7 | 8 | 9 | |
| **ENPV** | 124 | 127 | **132** | 134 | 131 | 128 | 126 | 126 | 100 |
| **Min NPV** | -15 | -15 | **7** | 1 | -7 | -13 | -8 | -21 | -66 |
| **Max NPV** | 272 | 266 | **266** | 266 | 266 | 266 | 266 | 266 | 251 |
| **Expected CAPEX** | 140 | 139 | **138** | 137 | 137 | 135 | 133 | 129 | 100 |
| **Initial CAPEX** | 75 | 66 | **66** | 66 | 66 | 66 | 66 | 66 | 64 |
| **Expected # of tiebacks** | 2.8 | 2.6 | **2.5** | 2.4 | 2.3 | 2.2 | 2 | 1.7 | 0 |

**Table 49:** Global sensitivity on the timing of enabling flexibility (strategy 8, RU only)

| | **Strategy 8** (% of ENPV or Expected CAPEX of strategy 1) | | | | | | | | **Strategy 1** |
|---|---|---|---|---|---|---|---|---|---|
| **Timing of enabling flexibility (Years)** | 2 | 3 | **4** | 5 | 6 | 7 | 8 | 9 | |
| **ENPV** | 171 | 172 | **177** | 179 | 177 | 172 | 160 | 142 | 100 |
| **Min NPV** | 27 | 22 | **22** | 19 | 12 | -7 | -19 | -37 | -66 |
| **Max NPV** | 329 | 327 | **335** | 331 | 322 | 316 | 305 | 293 | 251 |
| **Expected CAPEX** | 177 | 177 | **177** | 177 | 174 | 165 | 154 | 142 | 100 |
| **Initial CAPEX** | 75 | 66 | **66** | 66 | 66 | 66 | 66 | 66 | 64 |
| **Expected # of tieback fields** | 5.3 | 5.2 | **5.2** | 5.1 | 4.8 | 4 | 3 | 2 | 0 |

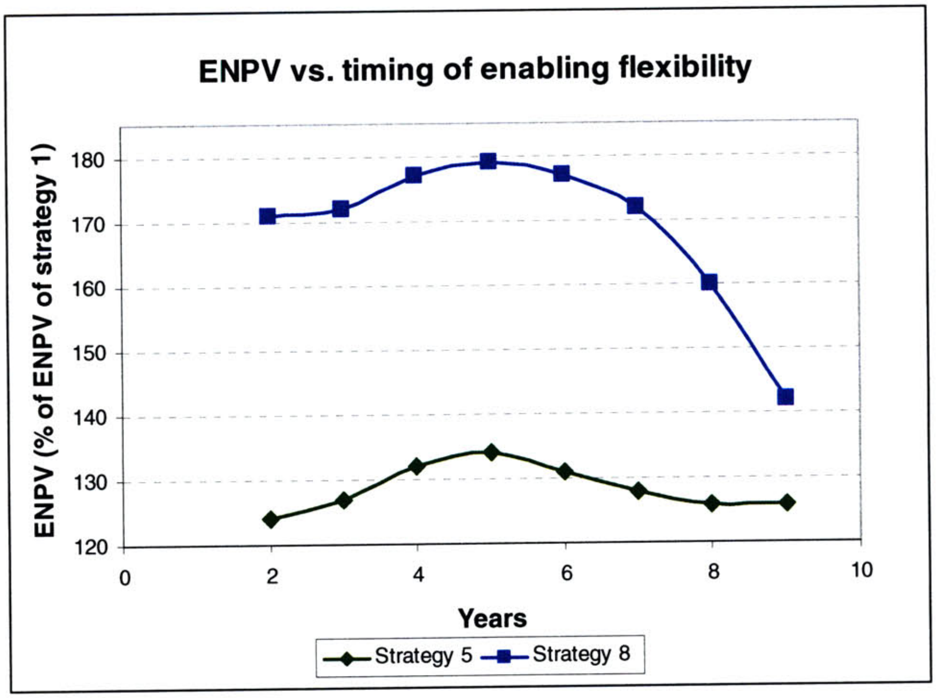


**Figure 90:** ENPV vs. timing of enabling flexibility

## 7.6.2 Local Sensitivity Analysis

The second type of sensitivity analysis is local sensitivity analysis, in which we introduce a small perturbation to the parameters and calculate the amount of change (or the gradient) of the ENPV with respect to the changes in the parameters.

**(a) Local sensitivity to the cost of tieback flexibility**

By perturbing from the nominal value for cost of tieback flexibility by a small amount ($\varepsilon$) from its nominal value, we can use the finite difference approach to calculate the local sensitivity parameter $\alpha^{ENPV\_5}_{\cos t\_of\_tieback}$ as follows:

$$\alpha^{ENPV\_5}_{\cos t\_of\_tieback}(10\%) = \frac{ENPV[(10+\varepsilon)\%] - ENPV[(10-\varepsilon)\%]}{2\varepsilon} \qquad \text{[Eq. 7 - 4]}$$

$$\alpha^{ENPV\_5}_{\cos t\_of\_tieback}(10\%) = \frac{ENPV(11\%) - ENPV(9\%)}{2} = \frac{130.17\% - 133.60\%}{2} = -1.72\%$$

$\alpha^{ENPV\_5}_{cost\_of\_tieback} = -1.72\%$ means that when the cost of tieback flexibility increases by 1% of the initial SURF cost, the ENPV decreases by 1.72% (based on the ENPV of strategy 1). This is a relatively large sensitivity value.

**Table 50:** Local sensitivity on the cost of tieback flexibility (strategy 5, RU only)

| | Strategy 5 | | |
|---|---|---|---|
| **Cost of tieback flexibility (% of the initial SURF cost of strategy 1)** | 9% | 10% | 11% |
| **ENPV** | 133.60 | 131.89 | 130.17 |
| **Min NPV** | 9.15 | 7.02 | 4.88 |
| **Max NPV** | 262.24 | 266.06 | 267.77 |
| **Expected CAPEX** | 137.88 | 138.47 | 139.05 |
| **Initial CAPEX** | 66.02 | 66.27 | 566.52 |

Similarly, we can calculate $\alpha^{ENPV\_8}_{cost\_of\_tieback}$. The results show that the ENPV of strategy 8 is more sensitive to the cost of tieback flexibility than strategy 5.

$$\alpha^{ENPV\_8}_{cost\_of\_tieback}(10\%) = \frac{ENPV[(10+\varepsilon)\%] - ENPV[(10-\varepsilon)\%]}{2\varepsilon} \qquad \text{[Eq. 7 - 5]}$$

$$\alpha^{ENPV\_8}_{cost\_of\_tieback}(10\%) = \frac{ENPV[11\%] - ENPV[9\%]}{2} = \frac{174.78\% - 179.09\%}{2} = -2.16\%$$

**Table 51:** Global sensitivity on the cost of tieback flexibility (strategy 8, RU only)

| | Strategy 8 | | |
|---|---|---|---|
| **Cost of tieback flexibility (% of the initial SURF cost of strategy 1)** | 9% | 10% | 11% |
| **ENPV** | 179.09 | 176.93 | 174.78 |
| **Min NPV** | 24.56 | 22.47 | 20.37 |
| **Max NPV** | 336.99 | 335.07 | 333.15 |
| **Expected CAPEX** | 176.18 | 176.94 | 177.70 |
| **Initial CAPEX** | 66.02 | 66.27 | 66.52 |

**(b) Local sensitivity to the cost of capacity expansion flexibility**

Similar procedures can be applied to calculate the local sensitivity to the cost of capacity expansion flexibility. Again, strategy 8 is more sensitive to the cost of capacity expansion flexibility than strategy 5.

$$\alpha^{ENPV\_5}_{cost\_of\_expansion}(0\%) = \frac{ENPV[\varepsilon\%] - ENPV[0\%]}{\varepsilon} \qquad \text{[Eq. 7 - 6]}$$

$$\alpha^{ENPV\_5}_{cost\_of\_expansion}(0\%) = \frac{ENPV[2\%] - ENPV[0\%]}{2} = \frac{130.13\% - 131.89\%}{2} = -0.88\%$$

**Table 52:** Local Sensitivity on the Cost of Capacity Expansion Flexibility (strategy 5, RU only)

| | Strategy 5 | |
|---|---|---|
| **Cost of capacity flexibility (% of the platform cost of Strategy 1)** | 0% | 2% |
| **ENPV** | 131.89 | 130.13 |
| **Min NPV** | 7.02 | 5.20 |
| **Max NPV** | 266.06 | 267.32 |
| **Expected CAPEX** | 138.47 | 138.99 |
| **Initial CAPEX** | 66.27 | 66.80 |

$$\alpha^{ENPV\_8}_{cost\_of\_expansion}(0\%) = \frac{ENPV[\varepsilon\%] - ENPV[0\%]}{\varepsilon} \qquad \text{[Eq. 7 - 7]}$$

$$\alpha^{ENPV\_8}_{cost\_of\_expansion}(0\%) = \frac{ENPV[2\%] - ENPV[0\%]}{2} = \frac{174.69\% - 176.93\%}{2} = -1.12\%$$

**Table 53:** Global Sensitivity on the Cost of Capacity Expansion Flexibility (strategy 8, RU only)

| | Strategy 8 | |
|---|---|---|
| **Cost of capacity flexibility (% of the platform cost of Strategy 1)** | 0% | 2% |
| **ENPV** | 176.93 | 174.69 |
| **Min NPV** | 22.47 | 20.20 |
| **Max NPV** | 335.07 | 332.95 |
| **Expected CAPEX** | 176.94 | 177.64 |
| **Initial CAPEX** | 66.27 | 66.80 |

However, ENPV is less sensitive to the cost of CPF capacity expansion than tieback flexibility cost changes. This confirms the earlier DOE results.

## 7.7 Modeling and Computation Effort

In this section, we will compare the modeling and computation effort between screening model and traditional high-fidelity models. It would require a significant amount of computation effort if high-fidelity models were used to simulate production profiles, facility cost, and project economics. For example, if a commercial reservoir simulator is used, each realization of the reservoir would possibility takes several hours or days to run on a desktop PC. Considering a Monte Carlo simulation with 1000 samples, the total simulation time can be a couple hundred days on a single processor. However, the integrated mid-fidelity screening model sacrifices some details (such as use tank model for generating production profiles) for speed and it focuses on interactions among reservoir, facility and project economics. For a screening model, each run only takes a few seconds and the whole Monte Carlo simulation (~1000 runs) can be done within an hour. Therefore, the screening model can be used to explore the large design space under uncertainty more efficiently. When several promising strategies are identified by the screening model, high fidelity models can then be applied to conduct detailed design studies and validate the most promising strategies.

Table 54 gives the summary of computational time, model setup time, and modeling time for this case study. The simulation environment is Matlab 7.4 on a laptop PC with an Intel Duo Core CPU @2.33GHZ and 2 GB memory. The computational time, setup time and modeling time for high fidelity models is based on engineers' experience in practice. Compared to high fidelity models, the screening model significantly reduces computational time, setup time, and modeling time.

**Table 54:** Computation time for screening models and high-fidelity models

| | | Computational time | | | | Setup time | Modeling time |
|---|---|---|---|---|---|---|---|
| | | 1 run | 200 runs | 2000 runs | 20000 runs | | |
| Screening models | Strategy 1 | 1.19 sec. | 238 sec. | 40 mins | 6 hours | Minutes ~ hours | Several weeks |
| | Strategy 5 | 1.87 sec | 374 sec. | 62 mins | 10 hours | | |
| | Strategy 8 | 2.65 sec | 530 sec | 88 mins | 14.7 hours | | |
| High fidelity models* | | 1 hour ~ days | 8~200 days | 0.22~5.5 years | 2.2 ~55 years | Weeks ~ months | months ~ a year |

On the other hand, we should also compare the loss of accuracy in the model due to the simplifications made in the screening models. However, the accuracy of models should be evaluated relatively during the different stages of a project. In the early stage of a project, high fidelity model do not necessarily always give more accurate results than mid-fidelity models because of the uncertainty in the inputs and models. A complex high fidelity model may not do any better than a simple screening model if the inputs and assumptions are wrong. The value of high fidelity models is primarily to support detailed engineering design and economics evaluation once promising strategies and architectures have been identified by screening models. Therefore, a screening model can add more value during a project's early stages (e.g., appraise and select stages in the oil and gas industry). The level of detail for a screening model needs to ensure that the rank order for different strategies is reliable for parametric assumptions that are deemed reasonable (as shown by global sensitivity analysis) with known or reasonable ranges of key parameters. As we illustrate in the sensitivity analysis sections in Chapters 6 and 7, the rank orders for flexible strategies are robust to the changes in the assumptions in the models (e.g., cost of options) and decision rules (e.g., timing of enabling flexibility). To apply this approach in practice, a complete set of sensitivity analysis would be needed to determine whether the modeling of strategies (including screening models, initial configurations, uncertainty models, and decision rules) achieves the desired level of detail.

## 7.8 Summary

In this chapter, a generic tieback field development framework is developed and then applied to a specific case study – the development of a hydrocarbon basin with multiple small oilfields with tiebacks. We applied the simulation framework to study different field development strategies under multi-domain uncertainty. The case study in this chapter demonstrates the processes of exploring flexibility in the early stages of field development.

- We identify and model key uncertain variables (e.g., reserve estimate, facility availability, and crude oil price) in multiple domains. In this case study, reservoir, facility, and market uncertainties have been identified and modeled using different stochastic process models. There are two types of stochastic models: one is to simulate human perception of uncertain variables in which the underlying true value does not change; the other type of stochastic model is to simulate how an aleatoric uncertain variable (e.g., crude oil price, facility availability) evolves by itself into the future in which the true value does change.

- Next, we propose a set of reference cases. In field development planning, it is very critical to identify several most likely cases as references. The development plans of the reference cases are based on the most likely value (i.e., mean, median) of the uncertain variables. Usually, the reference cases are deterministic and no flexibility is embedded. In this case study, strategy 1 (with 150 MBD capacity) and strategy 9 (with 175MBD capacity) are deterministic reference cases as a basis for comparison. For both strategies, all three levels of flexibility are disabled.
- Next, we evaluate the reference cases under uncertainty. The possible outcomes for reference cases need to be evaluated under both technical and market uncertainties. The distribution of outcomes and their statistics (e.g., ENPV) can be used as basis for comparison with other flexible strategies.
- Next, we identify a set of flexible options. Based on the reference cases, a set of flexible options can be identified. As we illustrate in Chapter 5, there are three levels of flexibility in complex systems: strategic level, tactical level, and operational level flexibility. For this case study, these three levels of flexibility correspond to inter-facility level flexibility, intra-facility level flexibility and ARM flexibility, respectively. We use Design of Experiments to set up a set of strategies by turn on or off specific types of flexibility.
- We develop and implement a set of decision rules to determine how flexibilities should be exercised, such as the number of decision branches in each discrete time step and what actions to be taken in each decision branch according to the estimate of the state vector $\hat{\vec{V}}(t)$. A set of decision rules needs to be pre-defined in order to simulate the flexible strategies. We can then experiment with and fine tune these decision rules by sensitivity analysis.
- We simulate a project's lifecycle value under uncertainty. An integrated screening model and simulation framework have been developed for this purpose. The screening model and simulation framework allow to evaluate the proposed strategies under uncertainty in a computationally efficient way.

- We then evaluate and compare different strategies in terms of the distribution of outcomes -- Value-at-Risk-Gain (VARG) curves. The VARG curve and the summary of statistics table give decision makers a holistic view of each strategy, such as expected NPV, min NPV, max NPV, initial CAPEX, and a summary of system architectures (e.g., number of tieback fields, reserves). In this case study, the most flexible strategies (8, 12) achieved an ENPV that was about a factor of 2.5 higher than the baseline case.
- Given the VARG curve results and DOE setup, we can quantify the Value of Flexibility (VOF) through the main effects. A Pareto plot of VOF shows the relative importance of each type of flexibility and their interactions. The results consistently showed that tieback flexibility had the largest contribution with between 55~65% VOF to total NPV. ARM flexibility further improves ENPV by 10~15% if tieback flexibility is enabled. The interaction effects show that the three levels of flexibility are not independent of each other. Some options cannot contribute value unless other types of flexibility are also present. For example, strategies with operational flexibility or capacity expansion flexibility only (such as strategies 2 and 3) cannot improve a project's NPV much if tieback flexibility is not enabled. This is because there are no additional fluids to operate on if there is no tieback.
- We conduct sensitivity analysis on key assumptions or parameters (e.g., timing of enabling flexibility, cost of option). Global sensitivity analysis gives the conditions at which the rank order of different strategies starts to cross over. Local sensitivity analysis gives the magnitude of change for the key economic metrics with respect to the changes in the parameters. Sensitivity analysis gives modelers and decision makers a confidence interval for the rank order of different strategies. Cost of flexibility can in many cases increase significantly (>30%) without changing rank order.
- Finally, we can compare strategies in terms of risk-return and gain-return plots. In this way, decision makers can easily identify different strategy clusters. The strategy cluster with high expected return, low risk, and high upside gain is preferable. After the promising strategies have been identified, high-fidelity models and discipline-based tools will be used to conduct detailed engineering design and economic evaluation.
- In this case study, we sequentially turn on reserve uncertainty, facility availability uncertainty, and market uncertainty and see their impacts on the VARG curves. Different

sources of uncertainty affect the results in difference ways: reservoir uncertainty shifts distributions horizontally; facility availability uncertainty affects all strategies equally by lowering NPV; market uncertainty tends to extend tails and dilute differences between strategies.

For the case study shown in this chapter, the flexible tieback strategies outperforms the deterministic case as it enables the field development to adapt to future uncertainty. Given assumptions for cost of tieback (10% of the initial SURF cost), tieback flexibility only requires small amounts of extra CAPEX initially and defers the implementation cost of tieback (such as well and SURF costs for tieback) into the future. Sensitivity analysis further confirms that tieback strategies remain competitive with non-flexible strategies until the upfront cost of tieback flexibility increases up to 40%. Platform capacity expansion flexibility allows the project to take upside opportunity and further improve project ENPV. In this particular case study, the simulation results suggest starting the project with a slightly larger platform capacity initially (175 MBD) and then using flexible tiebacks to bring more resources online in the future. But this is not a general recommendation for all circumstances. In some cases, especially when subsurface uncertainty is high, it may be better to start with a small platform and expand accordingly when subsurface uncertainty is reduced. In-depth analysis (e.g., sensitivity analysis) on the assumptions for the parameters in the uncertainty model (e.g., reserve evolution model) is a subject of future work.

# Chapter 8: Summary and Future Research

## 8.1 Summary

This thesis addresses the research opportunity of using screening models to identify and evaluate flexible architectures or development strategies for capital-intensive systems during the early stages of a project. The current oil and gas industry practices have the following limitations and do not effectively take into account multi-domain uncertainty during the conceptual study and development planning stages of a project:

- Traditional engineering practice designs and optimizes systems with fixed specifications and deterministic projections regarding the technical and market uncertainties. However, a point-optimal solution is no longer optimal if uncertainty evolves. Especially for capital-intensive systems with long lifecycles, the future operating conditions usually become very different from the initial expectations. Thus, a rigid point-optimal solution to the initial deterministic estimate will very likely lock a system into a configuration, which is not adaptable to future uncertainty.
- Current industry practice heavily relies on high-fidelity models to design each sub-discipline (domains) of the systems. High-fidelity models require significant amounts of engineers' time to set up, transfer data, and run simulations. The interfaces between disciplined-based models and tools are usually handled manually. Thus, a deterministic end-to-end model (e.g., resources systems, system designs, and project economics) and evaluation of the systems typically requires months or even years. Typically no more than ~3 configurations are studied. During this extended modeling lifecycle, the uncertainty may already evolve significantly, therefore, the results of high-fidelity models may become irrelevant to some extend when they become available.
- During a project's early stage, the knowledge of resource systems, potential system designs, and market conditions is very limited. The prediction of a high-fidelity model may neither be entirely accurate nor relevant due to uncertainty in the inputs and model assumptions.

Therefore, we developed and demonstrated a two-stage approach. The first stage is the use of an integrated mid-fidelity model to screen different strategies under multi-domain uncertainty and to identify promising strategies. By embedding flexibility in design, a project can better adapt to future uncertainty, in terms of reducing downside risk and capturing upside opportunity. Once promising strategies have been identified during the first stage, the second stage uses high-fidelity models to do detailed design and economic evaluation on the most promising designs and strategies. This two-stage approach reduces the cycle time of generating conceptual designs and identifies high value creation opportunity (e.g., multi-level flexibility) during the early stages of a project. This thesis concentrates on the first stage – screening flexible strategies under multi-domain uncertainty – of this two-stage process.

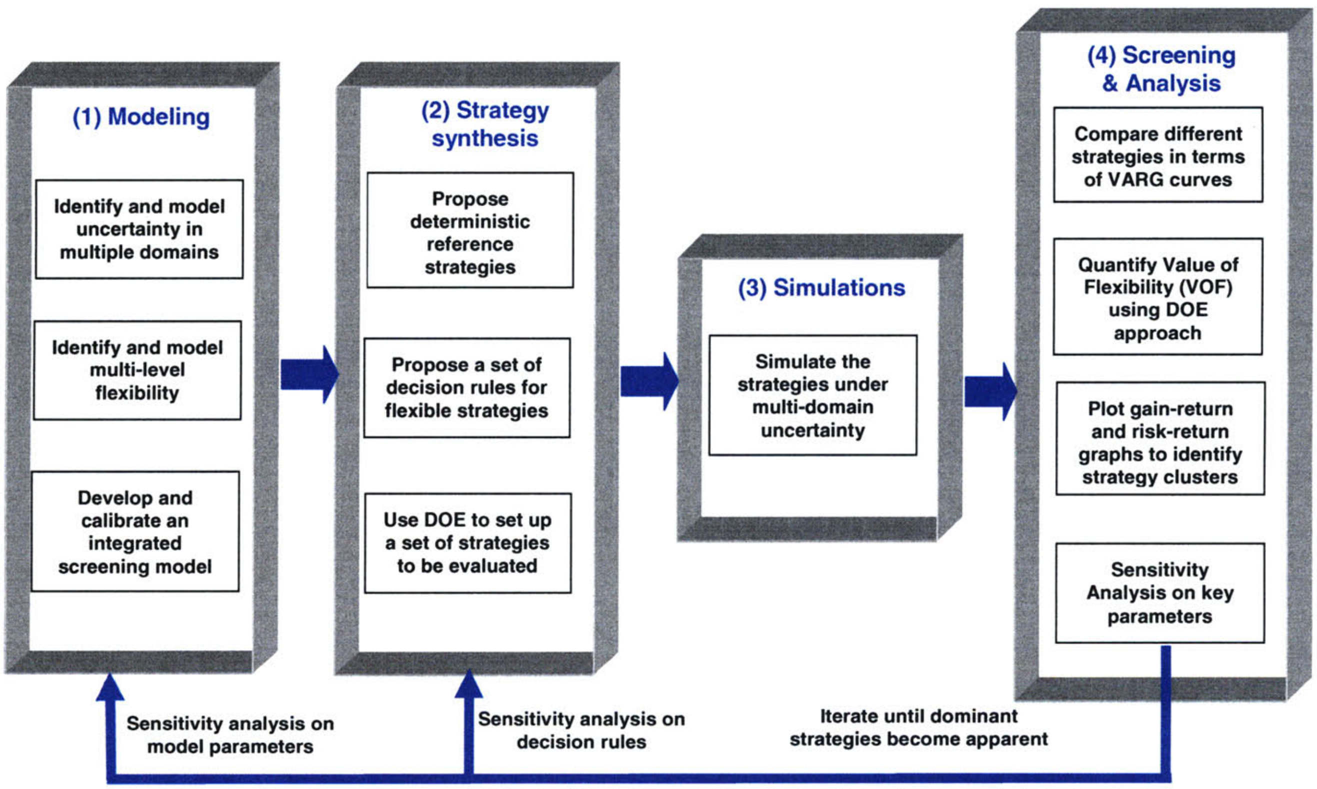


**Figure 91:** A generic four-step process for screening flexible strategies under uncertainty

Figure 91 shows a generic four-step process for screening strategies under uncertainty by using screening models. The four-steps are:

1) Modeling: The modeling step constructs a computational environment to experiment and simulate different strategies. It includes the identification and modeling of multi-domain uncertainty, multi-level flexibility, and an integrated screening model.
2) Strategy synthesis: Initially, designers or modelers need to come up with one or several reference cases, which are deterministic designs based on current best knowledge of systems and the uncertain factors. These strategies are used as a basis for comparison with flexible strategies. Then, modelers or decision makers need to propose a set of decision rules for flexible strategies. The decision rules are based on experience and not necessarily optimal initially. Finally, Design of Experiments can be used to generate different strategies by turning on/off or modifying features (i.e., flexibility) in the decision rules. This step sets up a set of strategies or design alternatives to be simulated and compared in steps 3 and 4.
3) Simulation: This is the core of the screening process. Figure 92 shows the underlying simulation framework. There are two iteration loops. The outer loop is a Monte Carlo simulation and each sample includes an instance of multi-domain uncertainty. The inner loop is a simulation run time iteration, which simulates the development and operation of engineering systems over their lifecycle. There is a decision making module built into the inner loop, which observes the evolution of multi-domain uncertainty and then modifies the screening models by exercising flexibility as appropriate. Hence, because the screening models are essentially time-variant, the resource systems and systems designs can be changed over the course of a project's lifecycle.
4) Screening and analysis: This step compares the alternative strategies from the simulation in terms of probability distributions of technical or economic metrics, such as Value-at-Risk-Gain (VARG) curves for projects' NPV. A good strategy should be able to shift the VARG curve of a deterministic reference case in favorable ways, such as improving ENPV, cutting the downside tail, and extending the upside tail. By using the DOE approach, we develop regression models for ENPV as a function of different levels of flexibility, and then we formally quantify the Value of Flexibility (VOF) by the taking difference in ENPVs between the flexible strategies and the inflexible strategies. A concise way to present the results to senior management is using risk-return and gain-return plots, in which different strategy clusters can be easily identified. Strategy clusters

provide sets of strategies instead of point-optimal solutions, and decision makers can compare and select the strategies that suit their risk-reward attitude (e.g., risk exposure on the initial CAPEX). Finally, sensitivity analysis allows modelers to fine tune the assumptions and parameters in the models and decision rules. The global sensitivity analysis provides the ranges of parameters within which the rank order of the strategies remain stable. The local sensitivity analysis gives the magnitude of change of the results with respect to the changes in the parameters.

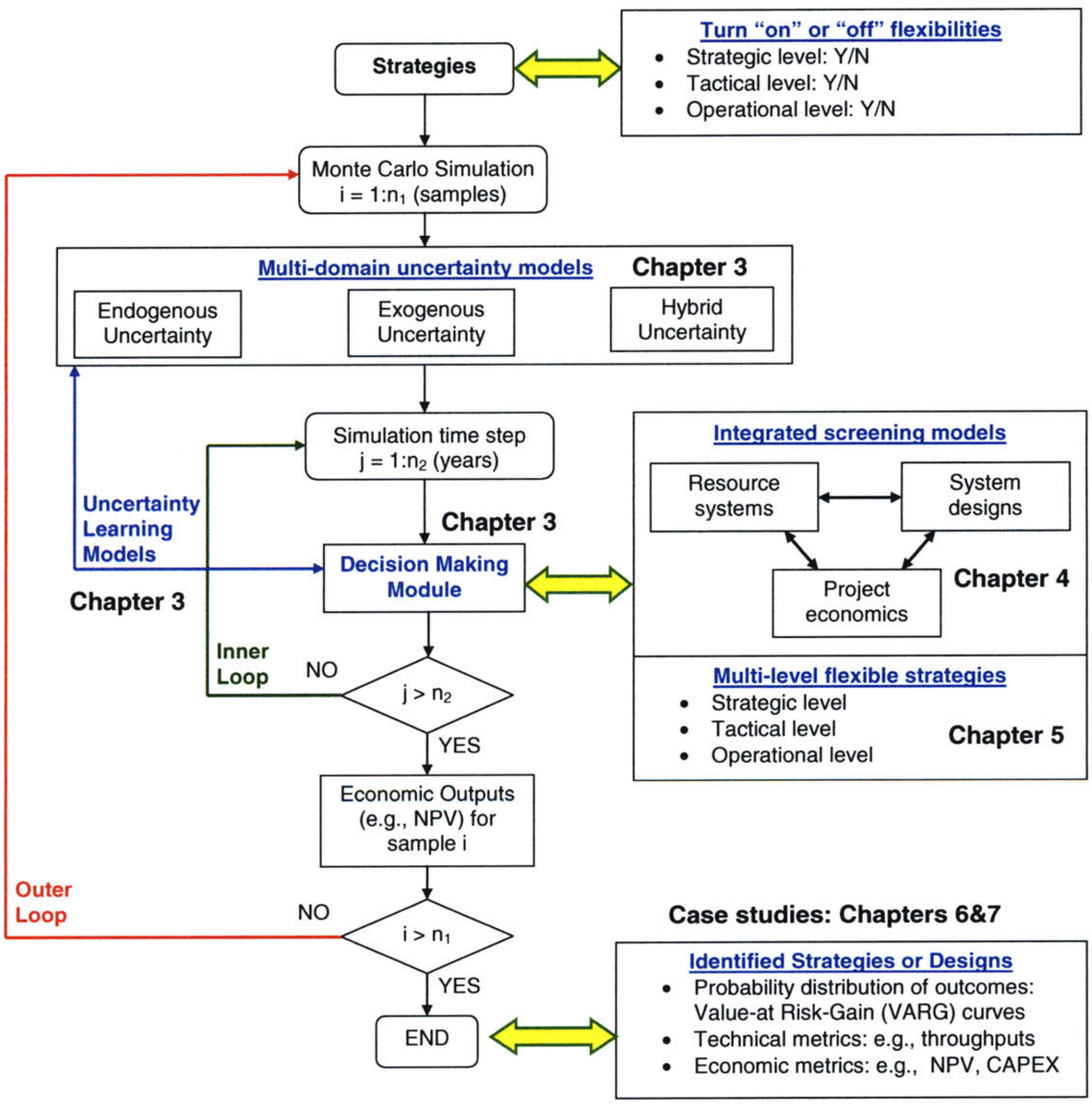


**Figure 92:** A simulation framework of using integrated screening model

## 8.2 Main Contributions

This thesis contributes to both the academic literature and industrial practice in the following aspects:

1. Multi-Domain Uncertainty Modeling
    a. Comprehensive discussion and modeling of multi-domain uncertainty focusing on technical-economic sources of uncertainty in the input system (reservoir uncertainty), production system (facility availability) and output system (market uncertainty such as crude oil price).
    b. Clear distinction between epistemic (reducible) uncertainty and aleatory (irreducible) uncertainty and modeling of human decision making based on the perception of the true values for epistemic uncertainty (i.e. reservoir/hydrocarbon properties).
    c. A reverse Wiener jump-diffusion process model to capture epistemic uncertainty decrease over time for reservoir estimates. It mimics the increase in knowledge over time (i.e. reduction of uncertainty), but still allows for the presence of discrete jumps.

2. Integrated Modeling Approach for Flexibility Screening Models
    a. Developed a 4-step process for developing, implementing and exercising mid-fidelity screening models to screen (filter) promising engineering systems development strategies. This 4-step process is a further development of the simpler 2-step process developed by Wang (2005).
    b. Developed and demonstrated a time-stepped Monte Carlo Simulation framework (essentially implementing step 3 of the above 4-step process, featuring two nested loops) to generate distributions of outcomes in the form of VARG curves. Although the VARG curves and MC simulation exist in current literature, the integration of these is a contribution of this thesis.
    c. Developed a generic form of decision rules for exercising flexibility inside the system lifecycle simulation, using an iterative decision tree approach. The

decision rules are formulated as Boolean statements that can trigger actions when certain pre-determined conditions are satisfied.

3. Appraisal and Selection of Offshore Petroleum Projects
    a. Developed mid-fidelity models for reservoir dynamics, facility availability and project economics at a comparable level of detail and integrated these in a Matlab implementation environment.
    b. Introduced the notion of multi-level flexibility (strategic, tactical and operational) flexibility in oil and gas projects. Demonstrated that these real options are not independent but coupled through interaction effects. Value of Flexbility (VOF) analysis attributes contributions to individual source of flexibility and their interactions.
    c. Developed a formal approach for modeling the tie-back flexibility problem (case study II, Chapter 7) and demonstrated that tie-back flexibility can add 55-65% NPV in multi-reservoir situations. Tieback flexibility is most valuable, followed by operational flexibility (ARM). The key was the main effects and interaction effect analysis and the implementation of a watercut-based fluid processing capacity allocation scheme.

## *8.3 Generalizability of the Framework*

The generic four-step process and simulation framework is generally applicable to capital-intensive projects, especially during the conceptual study and development planning stages. This thesis applied the framework to petroleum systems. Examples of other capital-intensive engineering systems include manufacturing and assembly plants for automobiles or aircraft, transportation infrastructures (e.g., highway, airports, railroads), and energy infrastructures (e.g., offshore petroleum systems, power grids, river dams). Although the models and case studies were all developed in the petroleum domain, the methodology and framework is applicable to other domains.

This generic framework should be applicable to other capital-intensive projects, such as development planning of manufacturing plants under multi-domain uncertainty in the automotive industry. In fact, the literature (Cooprider, 1989; Kidd 1998) in the automotive domain has addressed some key elements (e.g., multi-level flexibility) of the framework. We will use automotive manufacturing as an example to show conceptually how the framework could be applied to other domains.

**Problem statement**: Screening multi-level flexibility for development planning of automotive manufacturing plants.

***Integrated screening model:***

- Resource systems: a quantitative model of consumer demands for multiple market segments.
- System designs: plants' locations, capacities for each market segment. Cost models for plant, manufacturing equipment, suppliers, etc.
- Project economics: lifecycle value (i.e., revenue) and cost (CAPEX, OPEX, tax) model for manufacturing plants.

***Multi-domain Uncertainties***

- Endogenous uncertainty: uncertainty in manufacturing and production technology embedded into systems, such as product quality uncertainty due to variations in manufacturing and assembly processes. Decision makers can reduce endogenous uncertainty by investment in technology such as applying Stochastic Process Control (SPC), and installing Coordinate Measurement Machines (CMM) in assembly lines.
- Exogenous uncertainty: consumer demands for different market segments, the price of gasoline (changes demands for different models), the cost of the materials, suppliers, etc.
- Hybrid uncertainty: development time and schedule uncertainty in plant development. They are influenced jointly by decision makers and market forces.

***Multi-level flexibility:***

- Strategic flexibility: For development planning of multiple automotive plants, the strategic level flexibility may include the flexibility of assigning plants to different geographical locations, and the flexibility of allocating multiple models (market segments) to plants.
- Tactical flexibility: Similar to petroleum projects, plant capacity expansion flexibility is considered as tactical level flexibility. Tactical flexibility may also include switching flexibility, such as flexible manufacturing and assembly lines for multiple product variants.
- Operational flexibility: As market conditions evolve, plant operators can change production throughputs by varying shifts (i.e., 1, 2, and 3 shifts) to maximize profit. Operational flexibility is the flexibility to operate a system in different ways without changing the systems' configurations.

***Decision rules for flexible strategies:***

- Plant assignment decision rules: This is a strategic level decision which decides where and when to add new plants to global supply chain networks or when to shut down existing plants. Decisions may be driven by global and local market demand for vehicles and local labor costs and contracts.
- Decision rules for capacity: Once a decision is made to develop a plant, the next level of decision is plant capacity, number of vehicle variants for this plant, and any capacity expansion flexibility. This decision models tactical level flexibility within a plant.
- Operational decision rule: Operational decision rules determine how to operate a system to achieve the highest economic value, such as dynamically allocating production capacity for multiple variants, switching production sequences, operating on multiple shifts, etc.

From this qualitative analysis, we can see that the key concepts and elements of the framework are applicable to model and screen flexible strategies in development planning of automotive manufacturing plants. In recent years, major automakers have been facing severe technical and economic challenges of shifting production from SUV and pickup truck to small cars while crude oil prices have escalated. If manufacturing plants have built-in flexibility for switching production between different market segments, automakers could more easily modify the existing plants from producing SUV and pickup trucks to producing smaller cars. In a recent report in the Wall Street Journal (Sept. 23, 2008), Honda's manufacturing flexibility (e.g., switching models in assembly lines) in its plants allowed it to match consumer demand on small cars faster than its US rivals. Thus, this kind of research, such as exploring flexibility in manufacturing plants, can bring value to the automotive and other industries.

**Table 55:** Generalizability of the research framework

| | **Problem Statement** | **Integrated Screening models** | **Decisions** | **Uncertainty** | **Flexibility** |
|---|---|---|---|---|---|
| **Offshore Petroleum Systems** | Screening flexible strategies for offshore petroleum projects | • Reservoir<br>• Facility<br>• Project economics | • Field development architecture<br>• Facility concepts, capacity sizing<br>• Operations strategies | • Reservoir<br>• Facility<br>• Market<br>• Development (cost, schedule technology) | • Inter-field<br>• Intra-field<br>• Operational |
| **Automotive Production Plants** | Screening multi-level flexibility for automotive manufacturing plants | • Consumer/market demands models<br>• Products' performance, cost models<br>• Economics models for product families | • Global production plant networks<br>• Plant capacity, product segments/variants<br>• Operation decisions: i.e., line balance, assembling for mixed product variants. | • Market/ demand<br>• Technology<br>• Product quality /performance | • Strategic: market segments, plant locations<br>• Tactical: plant capacity and product variants<br>• Operational: i.e, dynamic line balancing |

## *8.4 Future Work*

The proposed generic process and simulation framework for screening flexibility under multi-domain uncertainty is part of an ongoing research stream in engineering systems design and real options "in" project. There are many opportunities to build on the work of this thesis and further advance this stream of research in the future:

1. <u>Technical uncertainty modeling</u>: A stochastic reservoir uncertainty model is proposed in this research, but the parameter estimates are not based on historical data of similar projects. One future research topic is to develop more realistic technical uncertainty models using historical data. One possible approach is to apply a Bayesian learning

framework to update model parameters as actual data becomes available. Ideally, the uncertainty and learning models need to be calibrated against historical data if available.

2. Value of Information (VOI): this model could be expanded to allow additional appraisal wells and seismic surveys to reduce upfront reservoir uncertainty. Such surveys and wells would cost upfront CAPEX and potentially delay "first oil" but reduce hydrocarbon uncertainty. In order to do this, an explicit relationship between appraisal CAPEX and the model parameters in Eq. 3-4 through 3-9 would have to be established.
3. Quantify cost of flexibility: The quantity *m* in Equation 4-14 was assumed to capture the effect of flexible options on CAPEX. A catalogue of real options in petroleum projects should be developed along with realistic cost models for the extra CAPEX of upfront flexibility.
4. Scenarios in quadrant "D": The existing models and tools should be generalized and applied to problems in the "D" quadrant of the problem landscape. These are scenarios with both multiple reservoirs and multiple facilities. An example of this would be to allow more than one CPF in the tieback case study of Chapter 7.
5. Define the model fidelity for screening models: This thesis develops an integrated screening model for petroleum projects at a mid-fidelity level. A mid-fidelity model ideally means a model just at the level of detail that the rank order of different strategies (i.e., VARG curves for multiple strategies) remains stable. In other words, adding any extra detail to the mid-fidelity model will not change the relative rank order of different strategies, but excluding any detail in the mid-fidelity model would change the ranking order. One of the future research directions is to formally test whether this criterion is satisfied for a mid-fidelity screening model and establish a model fidelity scale (similar to Technical Readiness Level (TRL) in Aerospace) for each domain.
6. Capture non-monetary flows: In this thesis, the main output provided by the mid-fidelity screening model is VARG (NPV distributions). While the economic metrics are very important for a commercial project, other flows may also be very important to stakeholders, such as emissions or jobs provided to the local economy. Multiple types of flows (e.g., monetary flow, social-political flow) should be included in future work and fed into formal stakeholder analysis.

7. Sensitivity analysis of VARG curves: The VARG curves are the main outputs of the analysis. The shape and rank order of the VARG curves depend on assumptions and parameters in the screening models, uncertainty models, and decision rules. In the thesis, we illustrate the global and local sensitivity analysis of the ENPVs to several selected parameters. One of the future research directions is to conduct more complete sensitivity analysis on other parameters in the screening model, the uncertainty models, and the decision rules.
8. Experimenting with and optimizing decision rules: In current research, the proposed decision rules are based on engineering experience and a trial-and-error approach. In the future research, more formal methods would be needed to formulate decision rules based on expert opinion and decision theory. Social science research methods, such as interviews and surveys, would be needed to obtain this kind of tacit knowledge from an organization. It also requires a formal way to capture decision spaces graphically and algorithmically. Some learning algorithms can be potentially developed to modify a decision rule during the simulation and thus enhance the performance of flexible strategies.
9. Integration with upstream architecture enumerators (e.g., OPN): Use of low fidelity models to generate the more promising system architectures development scenarios (i.e., upstream configuration generator, pre-screening models, automatic generation of architectural paths), such that they can be then modeled and evaluated under uncertainty by using the screening model.
10. Explore the impact of cost inflation (e.g., materials, services) on CAPEX and OPEX: Cost inflation influences whether the operating companies should pre-invest in capacity or allow for flexibility. This may require establishing an explicit communication between inflation in hydrocarbon (output) prices and (input) CAPEX for raw materials and services such as drilling and construction. Currently these quantities are assumed to be independent.

This thesis is part of the outcomes of a research project sponsored by a major energy company. In order to successfully implement the proposed framework, the author has several management recommendations:

- Data repository for modeling: Firms managing large capital investment projects under uncertainty should create a central repository of uncertainty related data such as technical uncertainty in the resource systems (e.g., reservoir), prices of raw materials, production costs, sales volumes, and prices of their products in various markets. Such a repository should be easily accessible by engineers and mangers. This kind of database should distill the uncertainty data into a form that is easy to understand and use by modelers.
- Integrated multi-disciplinary teams: Successfully implementing the framework would require close collaboration of multi-disciplinary teams. The traditional linear business process, such as subsurface team → facility team → commercial team → decision makers, is not efficient for business decision making during the early stages of a capital-intensive project. Information tends to get "lost" or under-utilized when handing over from one discipline team to the others. Furthermore, evolving uncertainty will likely make the effort (i.e., detailed design and analysis) of previous analysis invalid or irrelevant. Therefore, engaging multi-disciplinary teams during the screening phase is very critical for the success of implementing the framework. One possible model to foster multi-disciplinary team is to develop a Concurrent Design Facility (CDF) as it is now common in the aerospace industry (e.g., JPL Team X). Such a facility and associated modeling tools would be most valuable during the appraisal stage.

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# APPENDIX 1: Reservoir Model

This appendix summarizes the physics underlying the reservoir model used for screening.

## 1. Material Balance Equation:

The material balance equation relating produced volume of oil ($N_p$ stb) to the pressure drop in the reservoir ($\Delta P$) is given by:

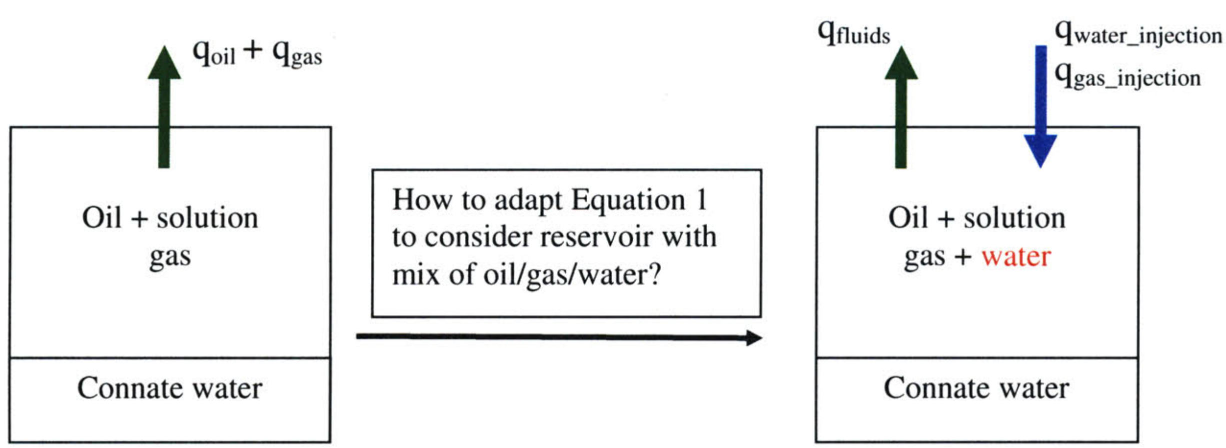
$$N_p\, B_o = N \cdot B_{oi} \cdot C_e \cdot \Delta P \qquad \text{(Eq. 1)}$$

Where

$B_o$ = oil formation volume factor at the reduced reservoir pressure [rb/stb]
$B_{oi}$ = oil formation volume factor at the original reservoir pressure [rb/stb]
$C_e$ = effective compressibility, volume averaged compressibility of oil, connate water and rock [$psi^{-1}$]
N = STOOIP: stock tank original oil in place [stb]

Assumptions and limitations of Equation 1:

- Solution gas drive reservoir above bubble point (unsaturated, no free gas in reservoir)
- No water injection
- No water (except connate water), so no water production
- Gas production (solution gas will liberate when oil gas mix come out of reservoir) is NOT captured in the equation.
- No gas injection
- No aquifer
- Reservoir fluid is perfect mix (homogeneous fluid) of oil with solution gas
- For pure solution gas drive, the reservoir pressure will drop below bubble point in the first few years, the Eq 1 will not be applicable afterwards. In other words, the "lifespan" of reservoir governing Equation 1 is just a couple years for only solution gas drive reservoir



Therefore, we need to develop a more generic material balance equation; at least it should able to deal with reservoir such as

- Produced fluids are mix of oil, gas and water
- With potential pressure maintenance mechanisms: such as water injection

## 2 Generic reservoir volume – production – pressure equation

This section will derive the generic reservoir – production – pressure equation (using water flood reservoir as an example). Instead of trying to "adapt" based on equation 1, let us start from the basic principle: "the driving force for production from reservoir" (Page 183, "Hydrocarbon exploration and production").

Isothermal conditions are assumed in the reservoir. Isothermal compressibility is defined as:

$$C = -\frac{1}{V}.\frac{dV}{dP}$$

Applying this directly to the reservoir, when a volume of fluid (dV, measured in reservoir barrels) is removed from the system through production, the remaining fluid expands to take up the "empty" space, which results in a drop in pressure (dP). The amount of pressure drop is determined by the effective compressibility of the mix fluids (oil, solution gas, water, and rock) according to their volumetric percentage (under reservoir condition). Therefore the fundamental equation is:

$$dV = R_{(i-1)} B_{mix}^{i-1} C_e^{i-1} dP \qquad \text{(Eq. 2)}$$

Where

$dV$ : the "net" volume of fluids (mix of oil, solution gas, and water) removed (production – injection) between time interval i-1 to i. The volume is converted into current reservoir volume through a mixed fluids formation volume factor: $B_{mix}$

$R_{(i-1)}$ : remaining reservoir volume (mix fluids) under standard condition at time i-1 [stb]

$B_{mix}^{i-1}$ : the effective formation volume factor for reservoir mix fluids at time iteration i-1 [rb/stb]. This relates the volume of fluid at standard conditions with no gas in solution to the volume occupied in the reservoir with gas dissolved in the solution.

Note: if we assume that the total reservoir volume (under reservoir conditions) remains constant (remaining fluids will expand to fulfill the empty space in reservoir as production occurs), $R_{(i-1)} B_{mix}^{i-1} = V_{r0} = const$ where, is initial reservoir volume in reservoir barrels.

$C_e^{i-1}$: the effective (total) compressibility of mix fluids at time iteration i-1

$dP$: the reservoir pressure drop as dV amount volume extracted within at iteration i

Let us write down each term in discrete form. The time elapsed between these two iterations is assumed as $\Delta t$

The net produced fluids (volume under reservoir condition):

$$dV = (q_{\_t} B_{mix}^{i-1} - q_{\_w\_in})\Delta t$$

Where

$q_{\_t}$: the average production rate of fluids oil (with solution gas) and water) in standard barrels at iteration i (or within the small time interval $\Delta t$) [stb] , the subscript t stands for total extracted fluids

Note: Convert liberated gas from [scf] to [stb] by multiplying 0.1781

$B_{mix}^{i-1}$: the effective formation volume factor for reservoir mix fluids at time iteration i-1 [rb/stb]

$q_{\_w\_in}$: the water injection rate at iteration i [stb=rb]. Since the injected water is invariably stripped of any gas prior to injection, therefore the surface and reservoir volume is the same.

So, we can rewrite equation 2 as:

$$(q_{\_t} B_{mix}^{i-1} - q_{\_w\_in})\Delta t = R_{(i-1)} B_{mix}^{i-1} C_e^{i-1} \Delta P \qquad \text{(Eq. 3)}$$

At time iteration i-1 to i, $C_e^{i-1}$, $B_{mix}^{i-1}$, $R_{(i-1)}$ need to be updated for the next iteration. The following will show how to update these parameters and variables.

The assumptions for this model and the following algorithm are:

*Assumption 1*: oil (with solution gas) and water are perfectly mixed and homogeneous.
*Assumption 2*: the single phase (fluids) exists in reservoir, in other words, no free gas in reservoir and oil is undersaturated.
*Assumption 3*: reservoir pressure is maintained above bubble point by water re-injection.

## Algorithm:

(Here we skip the first iteration, which basically uses the original reservoir condition as inputs, such as initial reservoir volume, pressure, composition of oil (with solution gas) / water, and formation volume factors).

The initial formation volume factor for mixed fluid in the reservoir is calculated by following equation:

$$B_{mix}^{0} = \frac{1}{\dfrac{{}^{r}S_o^0}{B_o^0} + \dfrac{{}^{r}S_w^0}{B_w^0}}$$

**Step (1): determine how much oil, gas, and water produced as mandated volume extracted at iteration i [stb]**

Here we use the parameters and variables from previous iteration i to estimate how much oil/gas/water is extracted. These parameters and variables will be updated in step 3 at the end of each iteration.

Given ${}^{r}S_o^{i-1}$, ${}^{r}S_w^{i-1}$, $B_w^{i-1}$, $B_o^{i-1}$ from the previous time iteration.

Given mandated total production rate for mixed fluid at iteration i: $q_{\_t}$

Given the time step for each iteration: $\Delta t$

According to assumption 1, the ratio of the amount of oil (with solution gas) to the amount of water produced is set according to their volumetric percentage at the reservoir conditions.

Given the volumetric percentage of oil, solution gas, and water at time iteration i-1 as:

${}^{r}S_o^{i-1}$: volumetric percentage of oil+ solution gas at iteration i at reservoir condition (r stands for reservoir condition)

${}^{r}S_w^{i-1}$: volumetric percentage of water at iteration i at reservoir condition

Note: ${}^{r}S_o^{i-1} + {}^{r}S_w^{i-1} = 100\%$ ${}^{r}S_o^{i} + {}^{r}S_w^{i} = 100\%$

Now, we need to convert the volumetric percentage from reservoir conditions to surface (or standard) conditions by using the formation volume factor for oil and water at the previous iteration.

$$ {}^{std}S_o^{i-1} = \frac{\dfrac{{}^{r}S_o^{i-1}}{B_o^{i-1}}}{\dfrac{{}^{r}S_o^{i-1}}{B_o^{i-1}} + \dfrac{{}^{r}S_w^{i-1}}{B_w^{i-1}}}; \qquad {}^{std}S_w^{i-1} = \frac{\dfrac{{}^{r}S_o^{i-1}}{B_w^{i-1}}}{\dfrac{{}^{r}S_o^{i-1}}{B_o^{i-1}} + \dfrac{{}^{r}S_w^{i-1}}{B_w^{i-1}}} $$

Where "std" stands for standard condition.

Therefore, the amount of oil, gas (solution gas liberates), and water at iteration i is:

Let $q_{\_t}$ defined as total fluid extraction rate [stb/day]

$$ \text{Oil}: \quad q^{i}_{\_o} \cdot \Delta t = q_{\_t} \cdot \Delta t \cdot {}^{std}S_o^{i-1} \qquad \text{[stb]} $$

$$ \text{Water}: \quad q^{i}_{\_w} \Delta t = q_{\_t} \cdot \Delta t \cdot {}^{std}S_w^{i-1} \qquad \text{[stb]} $$

$$ \text{Gas}: \quad q^{i}_{\_g} \Delta t = R_s^{i-1} \cdot q^{i}_{\_o} \Delta t = R_{si} \cdot q_{\_t} \cdot \Delta t \cdot {}^{std}S_o^{i-1} \qquad \text{[scf]} $$

Where, $R_s$ is the solution gas oil ratio (GOR, [scf/stb]), if reservoir pressure is maintained above bubble point, $R_s$ keeps as constant and equal to initial solution gas oil ratio -- $R_s = R_{si}$

**Step (2): calculate how pressure drops as production occurs at iteration i**

Given $C_e^{i-1}$, $R_{(i-1)}$, $B_{mix}^{i-1}$ from previous time iteration.

Given scheduled water injection rate at iteration i: $q_{\_w\_in}$

Plug in these into equation 3, we can how pressure changes ($\Delta P$)

$$\Delta P = \frac{(q_{\_t} B_{mix}^{i-1} - q_{\_w\_in})\Delta t}{R_{(i-1)} B_{mix}^{i-1} C_e^{i-1}}$$

Where $\Delta P = P_{i-1} - P_i$, $P_{i-1}$ is the reservoir pressure at the end of previous iteration i-1 (or the previous at the beginning of iteration i before fluids are extracted), $P_i$ is the reservoir pressure at the end of iteration i after the fluids are extracted)

So

$$P_i = P_{i-1} - \frac{(q_{\_t} B_{mix}^{i-1} - q_{\_w\_in})\Delta t}{R_{(i-1)} B_{mix}^{i-1} C_e^{i-1}} \qquad \text{(Eq. 4)}$$

Equation 4 describes how pressure drops as production occur between iteration i-1 to i

**Step (3): update reservoir "state variables" at the end of iteration i by taking account of volume extracted / re-injected.**

The state transition of reservoir includes:

- Percentage of oil (with solution gas) / water under reservoir conditions
    - Oil percentage (Volumetric percentage under reservoir condition) ${}^{r}S_o^{i-1} \rightarrow {}^{r}S_o^{i}$

      $${}^{r}S_o^{i} = \frac{(V_{r0} - q_{\_t}\Delta t B_{mix}^{i-1})\,{}^{r}S_o^{i-1}}{V_{r0}} \cdot \frac{V_{r0} - q_{\_w\_in}\Delta t}{V_{r0} - q_{\_t}\Delta t B_{mix}^{i-1}}; \qquad [\frac{rb}{rb}]$$

      Where $V_{r0} = R_{i-1} B_{mix}^{i-1}$, $V_{r0}$ is effective original reservoir volume in reservoir barrels, which remains constant: $V_{r0} = R_{i-1} B_{mix}^{i-1} = const$ for $i = 1,\ldots,n$

      Where $\frac{V_{r0} - q_{\_w\_in}\Delta t}{V_{r0} - q_{\_t}\Delta t B_{mix}^{i-1}}$ is volume expansion factor (expansion for occupying empty space creating by net effect of production and re-injection) for remaining reservoir volume in iteration i.

    - Water: ${}^{r}S_w^{i-1} \rightarrow {}^{r}S_w^{i}$

      $${}^{r}S_w^{i} = \frac{(V_{r0} - q_{\_t}\Delta t B_{mix}^{i-1})\,{}^{r}S_w^{i-1} \cdot \frac{V_{r0} - q_{\_w\_in}\Delta t}{V_{r0} - q_{\_t}\Delta t B_{mix}^{i-1}} + q_{\_w\_in}\Delta t}{V_{r0}} \qquad [\frac{rb}{rb}]$$

- Update the effective compressibility of mix fluids giving new oil/gas/water composition in reservoir:

  $C_e^i = C_o\,{}^{r}S_o^i + C_g\,{}^{r}S_g^i + C_w\,{}^{r}S_w^i + C_f$

  Where

  $C_o$: compressibility of oil with solution gas (assuming constant)

  $C_g$: compressibility of free gas in reservoir (assuming constant)

  $C_w$: compressibility of water (assuming constant)

  $C_f$: formation volume compressibility (generally small, become very small if reservoir pressure drop below bubble point)

The equation shown doesn't take into account of connate water. With consideration of connate water and assuming no free gas, the equation becomes:

$$C_e^i = \frac{(C_o\,{}^rS_o^i + C_w\,{}^rS_w^i)(1-{}^rS_{wc}^i) + C_w\,{}^rS_{wc}^i + C_f}{(1-{}^rS_{wc}^i)},$$

Once consider connate water, the problem become even more complicated, as the portion of connate water will expand as reservoir pressure drop and ${}^rS_{wc}^i$ will change over time. Given the fact that water compressibility is very small, let us assume ${}^rS_{wc}^i$ as initial value to make this problem simple.

- Formation volume changes:
  - Oil: $B_o^{i-1} \rightarrow B_o^i$

    $C_o = \dfrac{B_o^i - B_o^{i-1}}{B_o^{i-1}\Delta P}$, assume $C_o$ remains constant, and $\Delta P$ has been solved in step 1

    We can get:

    $B_o^i = C_o(B_o^{i-1}\Delta P) + B_o^{i-1}$ [rb/stb]
  - Water: $B_w^i = C_w(B_w^{i-1}\Delta P) + B_w^{i-1}$ [rb/stb]
  - Mix fluids:

    $$B_{mix}^i = \frac{1}{\dfrac{{}^rS_o^i}{B_o^i} + \dfrac{{}^rS_w^i}{B_w^i}}$$ [rb/stb]

  Note: the compressibility of oil (with solution gas) / water doesn't change much over time, but the effective compressibility of mix fluids might change significantly as the composition of oil/gas/water in reservoir change when water injection takes place.

- Percentage of oil (with solution gas) / water under standard conditions
  - Oil : ${}^{std}S_o^{i-1} \rightarrow {}^{std}S_o^i$

    $${}^{std}S_o^i = \frac{\dfrac{{}^rS_o^i}{B_o^i}}{\dfrac{{}^rS_o^i}{B_o^i} + \dfrac{{}^rS_w^i}{B_w^i}}$$
  - Water: ${}^{std}S_w^{i-1} \rightarrow {}^{std}S_w^i$

    $${}^{std}S_o^i = \frac{\dfrac{{}^rS_w^i}{B_w^i}}{\dfrac{{}^rS_o^i}{B_o^i} + \dfrac{{}^rS_w^i}{B_w^i}}$$
- Update remaining reservoir volume (in terms of standard barrels, although the reservoir pore volume or amount of reservoir barrels might remain constant).

$R_{i-1} \rightarrow R_i$ [stb]

$R_i = \frac{R_{i-1}B_{mix}^{i-1}}{B_{mix}^{i}} = \frac{V_{r0}}{B_{mix}^{i}}$;

where $V_{r0}$ is effective original / initial reservoir volume in reservoir barrels, which remain constant: $V_{r0} = R_{i-1}B_{mix}^{i-1} = const$ for $i = 1,\ldots,n$)

- Pressure changes – already shown in step 1 equation 4

  $P_{i-1} \rightarrow P_i$

## 3 Comparison of these two approaches:

**Approach 1**: material balance equation: $N_p B_o = N \cdot B_{oi} \cdot C_e \cdot \Delta P$ (Eq. A)
**Approach 2**: generic reservoir volume – production – pressure equation

$$q_{\_t}B_{mix}^{i}\Delta t = R_{(i-1)}B_{mix}^{i-1}C_e^{i-1}\Delta P \qquad \text{(Eq. B)}$$

Are they different?

For Eq. B
$R_{i-1}$: remaining reservoir volume (equal to initial reservoir volume) under surface standard condition at the end of time iteration i-1, [stb]
If t = 1, $R_{i-1} = R_o = N$: stock tank oil initially in place, $B_o^{i-1} = B_o^0 = B_{oi}$
$B_o^i$ and $C_e^{i-1}$ need to be updated within each time step.

**Case 1:**

If we choose incremental time step $\Delta t$ very small (e.g., one day), the difference between $B_o^{i-1}$ and $B_o^i$ becomes very small. So $\frac{B_o^{i-1}}{B_o^i} \approx 1$, and Eq B can be written as

$$q_{\_t} \cdot \Delta t = R_{i-1} \cdot \frac{B_o^{i-1}}{B_o^i} \cdot C_e^{i-1} \cdot (P_{i-1} - P_i)$$

$$\rightarrow \quad q_{\_t} \cdot \Delta t = R_{i-1} \cdot C_e^{i-1} \cdot (P_{i-1} - P_i) \qquad \text{(Eq. C)}$$

Eq. C is a special form of reservoir fluid compressibility equation: $dV = R_{(i-1)}B_{mix}^{i-1}C_e^{i-1}dP$

**Case 2:**

If we consider water injection within each time step, the Eq. B can be rewritten as:

$$(q_{\_t}B_{mix}^{i-1} - q_{\_w\_in})\Delta t = R_{(i-1)}B_{mix}^{i-1}C_e^{i-1}(P_{i-1} - P_i) \qquad \text{(Eq. D)}$$

Eq. A is a special form of Eq. B, Eq. D is more generic than Eq. C.

## 4 Total fluids production rate – $q_{\_t}$:

The total fluids production rate (mandated rate or reservoir natural decline rate) $q_{\_t}$ in equation 3 is determined by the following way:

$$q_{\_t} = \min(q_{well}(t), q_{platform}, q_{reservoir}(t)) \qquad \text{(Eq. 5)}$$

Eq. 5 states that the total fluids production rate is the minimal of three production capacity: well production rate, platform production capacity, and reservoir depletion rate at any given point of time t.

Where these production rate/capacity are determined by:

$$q_{well}(t) = \gamma \cdot N_t \cdot q_{\_w,t}$$
$$q_{platform} = \beta \cdot \max(q_{well}(t))$$
$$q_{reservoir}(t) = \frac{R_{(t)}}{R_0} \cdot N_t \cdot q_{\_w,t}$$

Where

$\gamma$: Well capacity utilization. [0, 1]

$N_t$: number of producing wells at time t

$q_{\_w,t}$: well rate at time t (in the model, we assume that well rate is constant and all producing wells are identical.)

$\beta$: relate topside platform production capacity as a portion of maximal well production rate. [0, 1]

$R_{(t)}$: (remaining) reservoir volume at time t

$R_0$: initial reservoir volume

$$q(t) = \frac{R(t)}{R(0)} \cdot q(0)$$
$$Q^{pot}(t) = n(t) \cdot q(t)$$
$$Q^{act}(t) = \alpha \cdot \min\left(Q^{pot}(t) \quad , \quad C_p(t)\right)$$

$q(t)$ is individual well production potential at time t

$R(0)$

$n(t)$

$Q^{pot}(t)$ is reservoir production potential, $n(t)$ is number of producers at time t

$Q^{act}(t)$ is actual production rate given platform capacity and system availability

$C_p(t)$ is platform capacity for total liquid rates

$\alpha$ is system availability [0 1]

## 5 Summary

Appendix 1 summarizes the physics underlying the reservoir model implemented in the screening model. This model assumes a reservoir as a homogenous tank with perfect mix of oil, gas, and water; and it also assumes the all well are identical with known initial total fluid production rates. Homogenous assumption can be relaxed (or improved) by introducing WOR and GOR correction coefficients. The derivation of the model is based on material balance equation with extension to considering water or gas injection. A generic reservoir production equation (Eq. B) is developed in this Appendix. Similar type of generic reservoir material balance equation can also be found in the classical text book[23] for reservoir engineering. We implemented a discrete version of this equation for the reservoir model in Matlab.

[23] Dake, L. P. *Fundamentals of Reservoir Engineering* (2nd ed.). Elsevier Science, 2001.

# APPENDIX 2: Facilities Model

**Facilities cost/weight modeling by Design of Experiments (DOE) and OGM**

The following approach illustrates the procedure how to use Design of Experiments (DOE) and Oil and Gas Management (OGM) software to develop a simple facility cost model. However, the regression model shows an extradinary Economies of Scale (EOS) due to a large constant term in the regression model. This large constant term stems from the constant substructure cost (steel jacket for SPJ or vessel for FPSO). It is a result due to assumptions in the default OGM models.

In this thesis, a standard EOS model (exponent 0.6) was used to calculate platform cost with smaller capacity. Therefore, this appendix only shows the general approach for developing facilities cost models. The regression model developed in this appendix is only used for calculating the platform cost with nominal capacity (100% capacity, ~200 MBD oil throughput). The platform costs with smaller capacities (75%, 50%, and 33%) are calculated based a standard EOS model (exponent 0.6) instead of using the regression model developed in this appendix.

**Model for Steel Pile Jacket Platform**

**Factors (independent variables):**

| | factor 1: $x_1$ Sea water depth (feet) | factor 2: $x_2$ Peak crude prod. Rate (mbd) | factor 3: $x_3$ Peak water prod. rate ratio | factor 4: $x_4$ Peak water inj. Rate ratio | factor 5: $x_5$ GOR (scf/bbl) |
|---|---|---|---|---|---|
| Lower level (coded: -1) | 200 | 100 | 0.3 | 1 | 500 |
| Higher level (coded: 1) | 1000 | 400 | 1.3 | 2 | 1500 |

Factor 1 ~4 are facilities design requirement given as inputs to OGM facilities modeling/simulation.

Notes:

Peak water prod. rate = peak crude prod. rate * peak water prod. rate ratio = $x_2 x_3$

Peak water prod. rate coincide with peak crude prod. rate = $0.3 x_2 x_3$

Peak water inj. rate = peak crude prod. rate * peak water inj. rate ratio = $x_2 x_4$

Facility: Steel Jacket Pile platform only for this pilot study

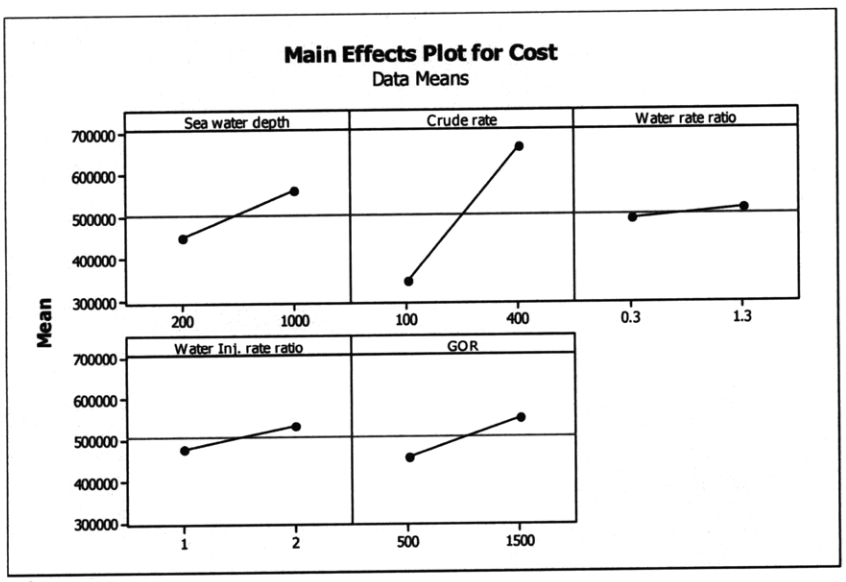
**Response (or dependent) variables:**

1. Field total cost (CAPEX): $y$

5 factors, 2 levels fractional factorial design: L-16

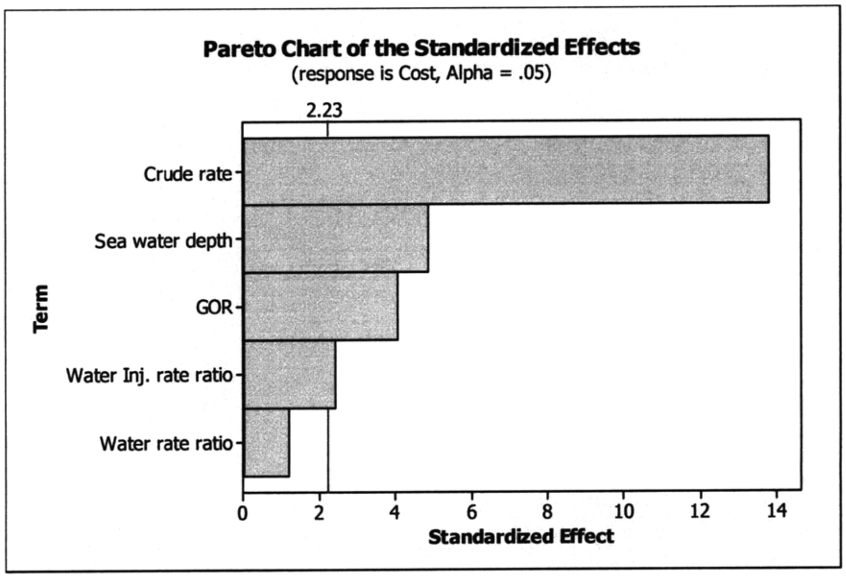
| **Experiment No.** | $x_1$ **Sea water depth (feet)** | $x_2$ **Peak crude prod. Rate (mbd)** | $x_3$ **Peak water prod. rate ratio** | $x_4$ **Peak water inj. Rate ratio** | $x_5$ **GOR (scf/bbl)** | **y Field total cost estimated by OGM ($:000)** |
|---|---|---|---|---|---|---|
| **1** | -1 | -1 | -1 | -1 | 1 | 292101 |
| **2** | 1 | -1 | -1 | -1 | -1 | 361771 |
| **3** | -1 | 1 | -1 | -1 | -1 | 468950 |
| **4** | 1 | 1 | -1 | -1 | 1 | 738205 |
| **5** | -1 | -1 | 1 | -1 | -1 | 268130 |
| **6** | 1 | -1 | 1 | -1 | 1 | 403381 |
| **7** | -1 | 1 | 1 | -1 | 1 | 653872 |
| **8** | 1 | 1 | 1 | -1 | -1 | 625241 |
| **9** | -1 | -1 | -1 | 1 | -1 | 283853 |
| **10** | 1 | -1 | -1 | 1 | 1 | 416953 |
| **11** | -1 | 1 | -1 | 1 | 1 | 699987 |
| **12** | 1 | 1 | -1 | 1 | -1 | 665958 |
| **13** | -1 | -1 | 1 | 1 | 1 | 325665 |
| **14** | 1 | -1 | 1 | 1 | -1 | 392641 |
| **15** | -1 | 1 | 1 | 1 | -1 | 591662 |
| **16** | 1 | 1 | 1 | 1 | 1 | 885373 |

## Main effects:




| | factor 1: $x_1$ Sea water depth | factor 2: $x_2$ Peak crude prod. Rate | factor 3: $x_3$ Peak water prod. rate ratio | factor 4: $x_4$ Peak water inj. Rate ratio | factor 5: $x_5$ GOR |
|---|---|---|---|---|---|
| Main effect (USD: 000) | 113163 | 323094 | 27273 | 56305 | 94666 |

Standardized effects:




From this analysis, the peak crude rate appears to be dominant factor, followed by sea water depth.

All factors are selected for regression model (the standardization effects chart suggests that water rate ratio is not significant, but it is not very far from the cut-off line, it is therefore included in the model)

**Regression model (coded)**:

$$y_1 = 504609 + 56581x_1 + 161547x_2 + 13637x_3 + 28153x_4 + 47333x_5$$

Where $x_i$, $i = 1 \sim 5$ scaled from -1 to 1. (Note, for prediction, need to transform real values into coded number)

**Regression model (uncoded)**:

$$y_2 = -50451.4 + 141.45x_1 + 1076.98x_2 + 27273.5x_3 + 56305.4x_4 + 94.67x_5$$

Where $x_i$, $i = 1 \sim 5$ take their real values.

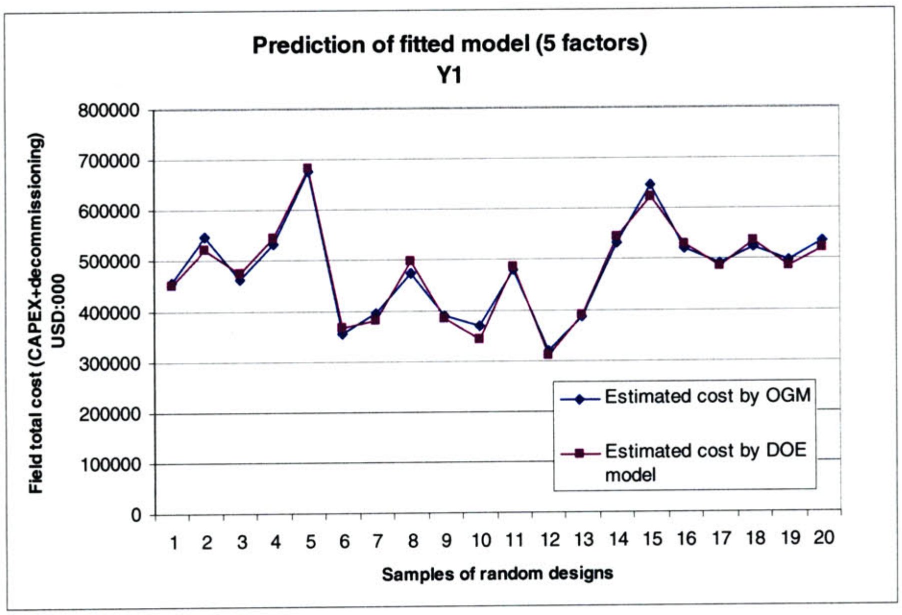
NOTE: This equation has extradinary EOS because OGM select the same substructure even the capacity is very small. The large constant term (e.g., 504609) in the coded regression model represents a fixed cost which is independent of platform capacity. In this thesis, we only use this regression to calculate the platform cost with nominal capacity (200MBD), but we apply a standard EOS formula (with exponent 0.6) to calculate smaller platform cost.

**Fitted model prediction study: compare OGM result and fitted model:**

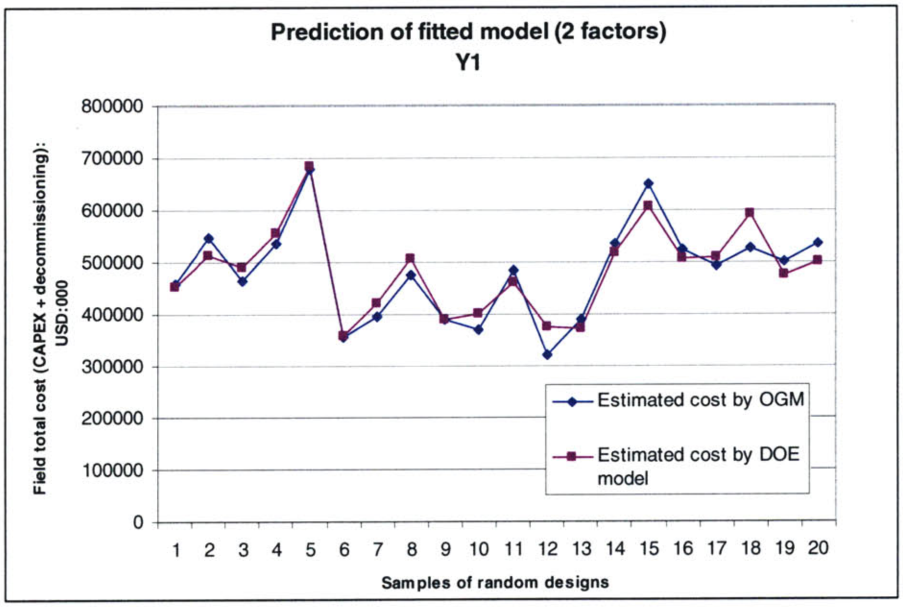
Steps:

- Generate 20 randomized design requirements by drawing factors 1~4 randomly from their ranges.
- Develop 20 OGM models by using these 20 randomized design requirements, and simulate the models to obtain field total costs.
- Apply fitted curve on these 20 designs and get field total cost estimations.
- Plot the OGM results and fitted model prediction on same graph and quantify the errors. 20 random designs

**Prediction results by using the fitted model (5 factors)**




**Prediction results by using fitted model (2 factors only: sea water depth and crude rate)**




**Conclusions:**

- The linear fitted model can represent the OGM internal cost estimation engine very well by using 5 factors.
- The two key factors --sea water depth and crude production rate – are main contributors to cost estimation model. But the including of other three factors – GOR, water inj. rate ratio and water prod. rate ratio – clearly improves the accuracy of the model.
- The crude production rate partially captures the effects of water prod. rate, water inj. rate, and gas production rate since these three rates are expressed as ratios based on crude production rate. Therefore, crude prod. rate is the main "sizing" factor for the whole system. The ratio based factors ($x_3, x_4, x_5$) are the "fine tune" factor for the subsystems (water prod. system, water inj. system, gas prod. & export system) given the overall system size expressed by the crude production rate.