# DESIGN FLEXIBILITY IN COMPLEX ENGINEERING SYSTEMS UNDER MULTIPLE UNCERTAINTIES

**JIANG YIXIN**

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# DECLARATION

I hereby declare that this thesis is my original work and it has been written by me in its entirety.
I have duly acknowledged all the sources of information which have been used in this thesis.

This thesis has also not been submitted for any degree in any university previously.

Jiang Yixin

10 August 2013

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## SUMMARY

Engineering systems are constantly facing various sources of uncertainty due to factors such as dynamic market place, evolving technology and changing operational environment. If uncertainties are not managed properly, they may cause large capital lost. Therefore, how to handle various uncertainties has become a pressing need for advancing the fields of system design. This is particularly motivated by recent rapid emergence of complex engineering systems which often feature intensive investment and long life. One important way to manage uncertainties is to incorporate flexibility/real options into the system design. Flexibility is a lifecycle system property which allows system to continue delivering value by adapting to unfolding uncertainties. Substantial efforts from a wide range of disciplines have been devoted to developing various flexibility designs, yet the issue of how to design flexibility in complex engineering systems under multiple uncertainties remains a challenging problem. It is in the context of this problem that this thesis designs a systematic framework for flexibility design.

This thesis proposes a two-stage decision framework to discover, value, and select real options "in" complex engineering systems under multiple sources of uncertainty.  A six-step screening process is proposed as the first stage to screen a system for locating the promising system elements for real options in the stage of real option identification. Firstly, a matrix-based simulation approach is proposed and utilized to analyze the change propagation behaviors and impacts of subsystems due to multiple sources of uncertainty. Secondly, two indicators, which measure the change propagation impact of a subsystem received and supply to others, are proposed. Based on the two proposed indicators and the identified cycle-causing subsystems, comprehensive recommendations are proposed to identify flexible subsystems and insensitive (robust) subsystems.

A practically implementable and theoretically consistent valuation approach is proposed as the second stage to assess the value of the embedded options with the objective of selecting the best combination of real options and determining the optimal timing to exercise the real options. The proposed valuation approach integrates Monte Carlo simulation and decision tree techniques. Numerical simulations have been conducted to demonstrate the effectiveness of the proposed approach.

The proposed two-stage decision framework has been demonstrated using an Unmanned Arial Vehicle (UAV) platform developed for multiple purposes. The results have confirmed the effectiveness of the proposed decision framework.

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| | |
|---|---|
| **CAPM** | Capital Asset Pricing Model |
| **C-FAR** | Change Favorable Representation |
| **CO** | Combined Opportunity |
| **CPD** | Cumulative Probability Distributions |
| **CPM** | Change Prediction Method |
| **CPI** | Change Propagation Index |
| **CPT** | Conditional Probability table |
| **CS** | Change Scenario |
| **DA** | Decision Analysis |
| **DAG** | Directed Acyclic Graph |
| **DCF** | Discounted Cash Flow |
| **DG** | Directed Graph |
| **DMM** | Domain-Mapping Matrix |
| **DOE** | Design of Experiments |
| **DPI** | Design Preference Index |
| **DSM** | Design Structure Matrix |
| **EG** | Event Generator |
| **ENPV** | Expected Net Present Value |
| **EI-R** | Environmental Impact-Received |
| **ESD** | Engineering Systems Division |
| **ESM** | Engineering System Matrix |
| **FMS** | Flexible Manufacturing Systems |
| **GBM** | Geometric Brownian Motion |
| **II-S** | Internal Impact-Supply |
| **LCC** | Life Cycle Cost |
| **LCV** | Life Cycle Value |
| **MAD** | Market Asset Disclaimer |
| **MCS** | Monte Carlo Simulation |
| **MDM** | Multiple-Domain Matrix |
| **PDE** | Partial Differential Equation |
| **PV** | Present Value |
| **ROA** | Real Options Analysis |
| **ROV** | Real Option Valuation |
| **SDE** | Stochastic Differential Equation |
| **UAV** | Unmanned Aerial Vehicles |
| **VCD** | Value Centric Design |
| **VDD** | Value Driven Design |

# 1 Introduction

## 1.1 Background

Currently, there has been growing research interest in designing and managing complex engineering systems, such as transportation networks, airport infrastructure, electrical grids, manufacturing supply chains, and health care delivery system. As understood by MIT's Engineering Systems Division (ESD), the term "engineering systems" mainly refers to (a) large-scale and socio-technical systems, which are composed of complicated interactions and designed by humans, with the purpose of fulfilling functional requirements of stakeholders and (b) the study of multidisciplinary approaches to address the engineering issues across social, political, environmental, and technical areas (ESD 2011). This research mainly involves the study of approaches to design and manage engineering systems and thus falls into the second meaning.

The "design to specifications", as a conventional paradigm, has been wildly accepted in many system engineering methods. In this paradigm, future uncertainty is rigidly projected into a small number of representative scenarios where requirements and operating conditions are pre-specified based on some probabilistic analysis (de Neufville, de Weck et al. 2004);optimization techniques are applied to maximize the expected value or minimize the life cycle cost (LCC) of a system; unexpected uncertainties are usually mitigated by employing risk management method, which focuses on eliminating possible negative consequences and lays emphasis on delivering reliable systems that "do not fail". The "design to specifications" paradigm restricts the engineering practice to only technical domain, while leaving the specification of value or performance of a system to its prospective owners or users (Hassan and de Neufville 2006). Moreover, it simplifies the system requirements to some fixed specifications.

Generally, the "design to specifications" paradigm remains suitable for systems which are designed and operated under relative stable or unchanging environments. However, it is insufficient in dealing with a large number of modern engineering systems with large scale and complexity. Over the last two decades, many engineering systems have become more complex, expensive and have longer life than ever before. The tremendous growth in scale and complexity of engineering systems has led to significant increase in the number of uncertain factors. These uncertain factors, which can be caused by changes in customer requirements, variety in economic conditions, viability of innovated technology, etc., greatly affect the lifetime value of the systems. Moreover, these uncertainties are further complicated due to the fact that most large-scale engineering systems are anticipated to have heavy capital investments and a long lifecycle. A representative example is the XM's spacecraft system which services in the United States and Canada, operated by Sirius XM Radio. It has a long expected lifetime of 17 years and requires an investment of over $600 million. Due to the wide variety of uncertainties, along with intensive capital investments and long lifetimes, the system development, operation and management have become more challenging. Moreover, the "design-to-specification" paradigm has become fundamentally flawed and inadequate when dealing with such expensive and complex systems with various uncertainties. The main reason is that it is beyond human's ability to specify the future requirements for complex technical systems explicitly when multiple uncertain factors vary extensively over years. Another important reason is that the "design to specification" paradigm narrowly focuses on preventing "technological failure" which will lead it to disregard uncertainties that create unexpected opportunities.

To rise to the challenge of the modern engineering systems featuring wide variety of uncertainty, intensive investment and long lifetime, the importance of effective and systematic uncertainties management has been attracted and it has attracted considerable research interests.

## 1.2 Motivation

Many brilliant and innovative researchers and practitioners have recognized that flexibility is a critical factor for increasing the long-term value or effeteness of complex technical systems over a wide range of uncertain scenarios. By adopting flexibility in the stage of conceptual design, designers can mitigate adverse risks and exploit attractive opportunities. Unfortunately, it is a challenging task to integrate the technical and operational flexibility to the system architecture. Currently system designers largely rely on their intuition and ad hoc methods. By this way, only simple flexible opportunities can be identified. Moreover, in practices, considering flexibility in a complex system design is not straight forward due to the fact that it requires explicit recognition of uncertainties, knowledge of the system in both technical and non-technical domains, as well as insight into the dynamic behavior of that system. This work is motivated by the need to develop a systematic way to facilitate the exploration, analysis and selection of most promising areas in physical aspect of the system to embed flexibility such that the flexible system is able to adapt to multiple sources of uncertainty and maintain a high value or performance over it long life time.

## 1.3 Flexibility in Engineering Systems

Flexibility has long been a key attribute in a variety of different fields, such as manufacturing (Sethi and Sethi 1990), infrastructure planning (Zhao and Tseng 2003), software architecture (Lassing, Rijsenbrij et al. 1999), product and organization design (Sanchez and Mahoney 2002), and information system (Byrd and Turner 2000). It refers to the ability of a system to change and adapt to environmental uncertainty. Saleh et al. (Saleh, Mark et al. 2009) provided an comprehensive review about the concept of flexibility in multiple disciplines and proposed a research agenda for designing flexible systems. In the field of engineering systems, flexibility is defined as the ability to cope with uncertainties, mitigate unfavorable risks and take advantage of upside opportunities.

Multiple sources of flexibility exist in engineering systems during their design and management stages. They are usually referred to as real options in literature. A real option is defined as a right, but not as an obligation, to take certain actions (e.g. deferring, expanding, contracting, switching and abandoning) in the future. Real options analysis (ROA) is one way to value flexibility by framing managerial flexibility or technical flexibility in terms of financial options. By valuing flexibility using ROA framework, the concept of flexibility is transformed into a quantifiable attribute of a system. According to the ways of exploiting flexibility in the engineering systems, there are two types of real options: real options "on" systems and real options "in" systems (Wang and De Neufville 2005). Real options "on" systems are related to managerial flexibility and provide decision makers the ability to make strategic decisions based on both current and projected environmental conditions. Different types of real options "on" systems are well identified and valuated in the literature. Research efforts in this field mainly focus on evaluating the flexibilities in project investments as well as on making strategic and capital budgeting decisions. The key feature of real options "on" systems is that engineering design and technology are treated as a black box. Real options "in" systems, on the other hand, is related to technical flexibility, and created by changing or modifying technical design of a system in order to adapt to changing technologies and operational conditions. Identifying real options "in" systems requires a good understanding of the system components and their interactions inside as well as outside the system. Real options "in" systems are able to enhance system performance by providing contingent decisions which limit a system's exposure to downside risks and capitalize the system under favorable conditions. For example, in a case study of a satellite communications system (De Weck, De Neufville et al. 2004), candidate architecture designs for satellite system are developed in different stages to meet the demand under various scenarios. When the demand increases, additional satellites are launched. If the demand drops, further investment is suspended or even canceled. Furthermore, the higher the uncertainty is, the more value the flexible system provides. However, the value of flexibility is associated to a cost. Therefore, proper evaluation techniques should be applied to assess how much flexibility to embed into the system and what strategies to take in order to maximize the overall value.

While traditional design focus on an optimal point design, the methods for flexibility “in” systems attempt to explore various kinds of design alternatives in the design space at the conceptual design phase, and delay critical design decisions until exogenous uncertainties are resolved or new information become available (Silver and de Weck 2007). Flexibility or real options “in” systems is the study of how to identify the sources of flexibility and how to develop an appraisal mechanism to assess and select them (Cardin and De Neufville 2008). It allows for a system change, and may not contribute to system value if left unexercised. Identifying real options within the technical systems requires a good understanding of the system and modular architecture. They may exist in the system or be incorporated on purpose by overdesigning some components of the system to enable future system modifications and evolutions Building a parking garage (Richard de Neufville, Scholtes et al. 2006) is a representative example. An initial four levels of parking garage with reinforced footings and columns is built to accommodate the current demand, and additional floors can be added later if future demand grows. Options embedded in the systems will increase initial construction costs. Higher initial cost will need to be invested to acquire more options for flexibility.

## 1.4 Staged Strategies for Flexibility

Based on historical study of engineering system design, staged or flexible platform strategies are common ways to incorporate flexibility in a system. During the lifetime cycle of the system, staged deployment strategies are made progressively to optimize total system value, starting with a platform-like initial design which provides capability to meet current requirements. When uncertainty is resolved or new information become available, critical decisions are made to whether to transit the system from the current state to the next state by changing non-standard or modular elements. System states refer to different scenarios, applications, mission and operational modes for which the system can be used (Cardin, Nuttall et al. 2007). The ability to reconfigure modular components or sub-systems of a fielded system after initial deployment represents technical flexibility in the system. One of the key advantages of staged deployment strategies is that it avoids locking systems into all-at-once configurations, which are difficult to be adjusted to meet future needs. Examples of embedding flexibility in a system via staged deployment can be found in many research papers (De Weck, De Neufville et al. 2004; Wang and de Neufville 2005; Hassan and de Neufville 2006; Richard de Neufville, Scholtes et al. 2006).

Options for flexibility enable staging of design decisions at the subsystem level or at the system (architectural) level. In former case, each design alternative can be viewed as “an instantiation of one system with modified subsystems”, and the switch costs are caused by changing among those subsystems (Silver and de Weck 2007). The optimal design variables for each alternative subsystem are chosen from Pareto-set in different scenarios where exogenous uncertainties are fixed. By contrast, configuration changes at the entire system architectural level are more radical. The possible transition paths between the initial architecture to higher capability ones have to be identified and understood in order to optimize overall system performance or value. This poses new challenging and complex problems to the designers. The first problem is that the configuration of the architectural at every stage may not be Pareto-optimal. The non-dominated designs on the Pareto efficient front are the ideal candidates for staged deployment. However, the transitions between those designs are not necessarily feasible. This is because the numbers of design degrees of freedom for evolutions in subsequent stages of the system are reduced by initial configuration in the previously deployed stages. The second problem is that the switching cost to pay for the embedded options "in" systems and the associated switching risk are not able to be quantified easily. The reason is that the designers may be unclear or unable to accurately model the risks associated with changing the technical configurations, organizational setting, or introducing new technologies. These two problems can be addressed through explicitly assessing the value of flexible system under staged deployment using real option valuation (ROV). The valuation process can provide not only the decision on whether or not to incorporate the flexibility in system design but also the possible transition paths of the system status as well as transition timing for system management.

However, ROV does not provide insights into which components and/or subsystem inside the initial system architecture should be modified or replaced to allow systems to adapt to multiple sources of uncertainties. It rather provide a way to quantify the financial value of real options, thus help to determine the optimal set of options and their optimal exercise timing under different scenarios of future uncertainty. This research focuses on embedding flexibility/real options in engineering system and staging design decisions at the system (architectural) level. The real options identification and valuation are integrated to provide a holistic study of real options "in" complex engineering system.

## 1.5 Research Question

While the staged strategies for embedding technical flexibility in engineering systems are appealing, the identification of appropriate initial platform-like design and possible design alternatives, as well as valuation and selection of optimal deployment strategies for complex engineering systems are non-trivial. Several issues involved in the research of real options “in” engineering systems are discussed in more detail as below.

1. Real options identification: It is challenging to determine where to embed flexibility and how to differentiate among these flexible opportunities in a complex system on the early conceptual stage. First of all, there is no well-defined set of real options “in” complex system (Cardin and De Neufville 2008). The reason is that every system is different and unique. Secondly, the issue of identifying where to embed flexibility “in” systems is difficult due to the fact that modern engineering systems have become much more capital intensive and highly interconnected. Complex engineering systems usually include a large number of system elements (e.g. subsystems, system components). It is a great challenge to make technical modification in system elements for flexibility due to the complex interactions among them. A technical change in one system element may trigger a series of changes in others and even result in system instability or a large capital cost. Thus, change propagation prediction is required to assess the value and risk of such change in a particular system element. However, predicting change propagation and its impact is further complicated by the complex interactions of system elements with multiple sources of uncertainty during system’s operational environment.

2. Real options valuation: Despite the wide acceptance in academic sectors and the growing implementations in practice, the implementation of ROV approaches for assessing various industrial projects and complex

engineering systems is still limited due to the significant gaps between theory and practices. First of all, a number of practical ROV approaches, which have been adopted by real options practitioners, lack consistence with financial theory. Secondly, the theoretical ROV requires rigorous assumptions of “perfect markets”, which renders them inapplicable in reality. In addition, practical approaches trade accuracy for computational simplicity. Binomial lattice/tree with limit discrete steps has been widely employed in ROV practices. It is able to evaluate multiple flexible decisions by simply inserting decision node into its branches. But it is not able to handle multiple uncertainties. On the contrary, Monte Carlo simulation is able to handle multiple uncertainties and provide accurate statistical results, such as distributions for further risk analysis. But it has high computational complexity, which hinder its application in valuing various types of real options.

## 1.6 Research Objectives

The main objective of this research was to develop a systematic and comprehensive methodology for designing, valuating and managing flexibility “in” complex systems influenced by multiple sources of uncertainty. The specific objectives of this research were to:

1. Provide a simple, fast and accurate change prediction approach for depicting change propagation and its impact on system elements with multiple sources of uncertainty.
2. Screen and recommend the promising system elements which can be changed easily or rapidly (flexibility), and the promising elements which are insensitive towards change (robustness), based on the change propagation analysis.

3. Provide practically applicable and theoretically consistent valuation approach for evaluating and selecting multiple real options "in" complex systems, hence provide the optimal timing to exercise these options in the management stage of flexibility.

## 1.7 Research Approach

This research has developed a comprehensive, two-stage integrated flexibility framework to exploring, valuing, selecting and implementing real options "in" complex engineering systems, as illustrated in Figure 1-1.

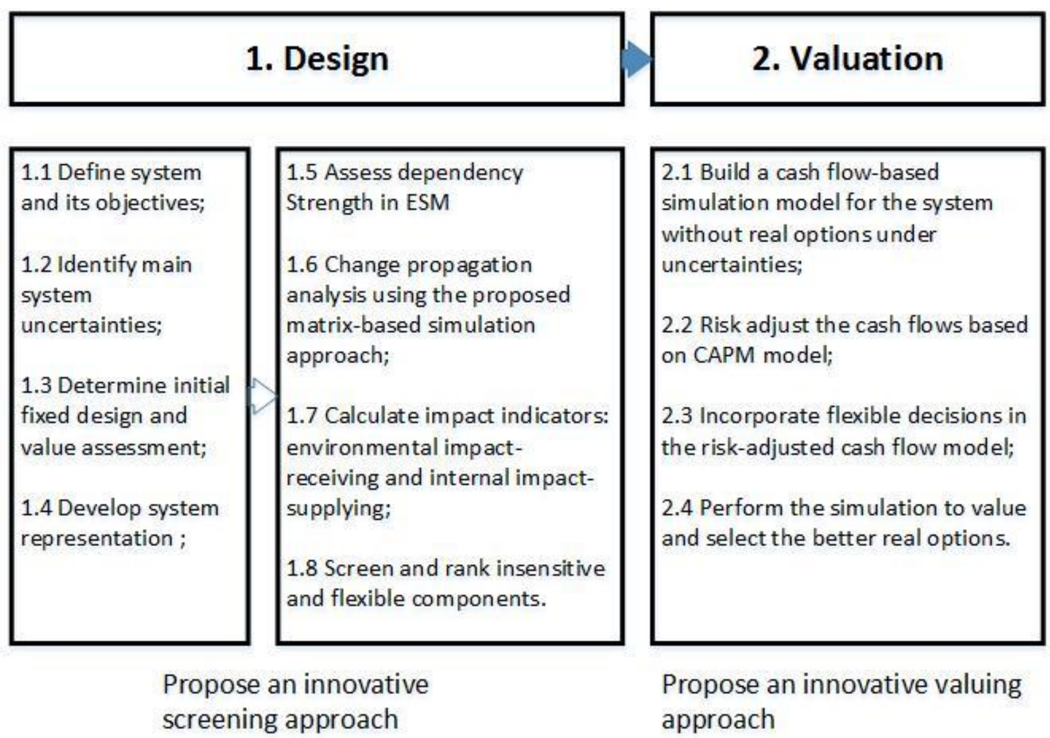



**Figure 1-1 Proposed real options framework**

In the design stage, a practical used and accurate matrix-based simulation approach was proposed to predict the direct and indirect change dependency among system elements under multiple environmental uncertainties. A six-step screening process using the developed simulation approach was proposed to search promising physical elements (e.g. system components and subsystems) where flexibility can be incorporated in by making technical modification in the initial design. The elements which cause the cyclic effects are identified and their impacts are re-estimated in the formulation of real options based on change propagation analysis. The candidate components for robustness and flexibility are screened and recommended according to two proposed indicators: environmental impact-received (EI-R) and internal impact-supply (II-S).

In the valuation stage, a risk-adjusted cash flow simulation based approach was proposed. The merit of this approach is that it is practically implementable. Moreover, it is consistent with the financial theory. From a practical perspective, the proposed approach can be implemented based on a cash flow model and only requires minimal subjective estimation with respect to input parameters. From a theoretical perspective, the approach properly accounts for both systematic and project-specific risks by risk adjusting the cash flow based on CAPM model, and thus it is able to provide a correct valuation from a diversified invertors' viewpoint. Moreover, by integrating Monte Carlo simulation and decision tree technique, the proposed approach is capable of incorporating multiple sources of uncertainty, evaluating the various types of real options and providing statistic results (e.g. distributions, standard deviation) for further risk analysis. The valuation process not only provides value of the options for selection of the best ones but also provides the decisions on the optimal timing to exercise the real options.

# 1.8 Thesis Outline

This chapter presents the research background, objective and the overview of the proposed approach. The remainder of this thesis is organized as follows:

Chapter 2 firstly reviews the concept of value driving designs. Subsequently, the concept of flexibility is introduced. Thirdly, general frameworks for real options are reviewed. Fourthly, methodologies and techniques for real options identification and valuation are reviewed. Then the research gaps are identified.

Chapter 3 presents a six-step screening approach for real options identification in complex engineering systems.

Chapter 4 presents a risk adjusted Monte Carlo simulation integrated with decision tree approach for real options valuation in complex engineering systems.

Chapter 5 formulates presents a case study of UAV manufacturing project. Both the real option identification approach proposed in Chapter 3 and real option valuation approach proposed in Chapter 4 are applied to demonstrate their effectiveness.

Chapter 6 summarizes the work done in this thesis and discusses the future research directions.

# 2 Literature Review

## 2.1 Introduction

In the previous chapter, the need to embedding flexibility in systems under various uncertainties is highlighted. This chapter presents the review of the literature pertinent to this work to provide the intellectual foundation both in theory and practice. Since this work is multidisciplinary at its core, knowledge from diverse disciplines (e.g. system engineering, decision analysis, risk management, finance valuation, engineering design, etc.) are covered in this section. First, the concept of value driven design (VDD) as the theoretical construct for flexibility, and recapitulate some of the key ideas related to VDD, are introduced.

## 2.2 Value Driven Design (VDD)

In the last two decades, the design community has seen a shifting perspective from fulfilling functional requirements to making best decisions to provide the greatest value to stakeholders. In traditional system engineering process, system engineers focus on optimizing a point design to achieve system capabilities specified in a wide variety of requirements while minimizing life cycle cost (LCC). Uncertainty with respect to meeting user needs and want is managed by "best guess" extrapolations of current and future requirements, even though the forecasting of future is "always wrong". To meet changing requirements and operating conditions, the requirement driven design methodology would lead to a more complex point solution with a significant incensement in cost, often resulting in cost overruns and unexpected schedule extension.

In contrast, VDD place an emphasis on maximizing the stakeholder value of a system. VDD is defined as “A proposed improved design process that uses requirements flexibility, formal optimization, and a mathematical value model to balance performance, cost, schedule, and other measures important to the stakeholders to produce the best outcome possible” by the American Institute of Aeronautics and Astronautics (AIAA), through a program committee of government, industry and academic representatives. In parallel, an identical design strategy, called value centric design (VCD) is developed by the US Defense Advanced Research Projects Agency (DAEPA). The terms VDD and VCD are interchangeable in this work. The essence of these two strategies is that good design decisions are made to provide the greatest stakeholder value rather than to merely satisfy requirements at lowest cost. VDD focuses on requirements flexibility and enable discovery of the best design configurations by maximizing system value in the entire solution space under uncertainties.

One key focus of VDD is the lifecycle value. In this work, the term “value” is defined as relative worth, utility, importance or quality of a thing with respect to its power and validity for its purpose or effect (Ross 2006). Two questions are generally concerned in respect of studies in value: “value for whom” and “best value according to what”.

# 2.3 Flexibility

## 2.3.1 Definition

Flexibility has been viewed as a critical concept in multiple disciplines, particularly in most design efforts in engineering and management (Saleh, Hastings et al. 2003). A variety of definition for flexibility concerning system or project design exists, and there is no uniformly accepted definition. However, most of these flexibility definitions are quite similar. (Fricke and Schulz 2005) characterize flexibility as "a system's ability to be changed easily [by external agents]… to cope with changing environments." The ESD symposium committee (Committee 2007) of MIT describe flexibility as "the ability of a system to undergoing changes with relative ease in operation, during design, or during redesign." (Nilchiani and Hastings 2007) describe flexibility as "the ability of a system to respond to potential internal or external changes affecting its value delivery, in a timely and cost-effective manner." From these definitions, it can be seen that flexibility is generally understood as the ability of a system to handle uncertainty by improving system performance with relative less effort (i.e. penalty in cost, time, or schedule).

### 2.3.2 Flexibility and Other "ilities"

There are three other "ilities" (usually but not always ending in "ility") which are close linked to the concept of changeability: agility, adaptability, and robustness. These four "ilities" are subsets of changeability(Fricke and Schulz 2005). Changeability is defined as the ability of a system to change its form or function in response to environmental uncertainties with acceptable expenditure. Agility is a system's ability to be changed rapidly. Adaptability is a system's ability to adapt itself (without external actuation) towards changing environments. Flexibility is a system's ability to be changed easily by external actuation. Robustness is the ability of a system to be insensitive and continue delivering value towards changing environments. Flexibility, adaptability and agility all refer to the ability of a system to be changed. They can be distinguished by change agents and degree of changeability needed.

Flexibility and adaptability are differentiated by asking who or what (change agent) instigate the change in the system. If a change in the system is instigated by a change agent who is internal to the system (i.e. the system recognized a need and changes itself autonomously without any external actuation), it is characterized as an adaptability-type change. If a change in the system is instigated by an external actuation implemented by an external change agent, it is characterized as a flexibility-type change. Therefore, the distinction between these two "ilities" relies on the location of the change agent with respect to the system boundary: insider (adaptable) or outside (flexible).

It is much easy to distinguish flexibility and agility. Both flexibility-type change and agility-type are required implementation of changes from external necessary. These two "ilities" are differentiated by asking how much changeability has to be incorporated; e.g. is flexibility sufficient for a system to react towards changing environment, or a system is required to react rapidly?

Despite this difference, flexibility, adaptability and agility are quantified and valued in the same way. For the purposes of this research the term *flexibility* is used as a broader concept of changeability which also includes adaptability and agility.

## 2.3.3 Flexibility in Different Disciplines

Saleh Mark et al. (2009) provide an elaborate literature review of flexibility in multiple disciplines, such as decision theory, real options, manufacturing systems and engineering design. Four distinct fields are selected for detailed literature review: decision theory, management, manufacturing systems, and engineering design.

### 2.3.3.1 Flexibility in Engineering Design

The concept of flexibility in engineering design is the main focus of this thesis. Multiple sources of flexibility are intentionally embedded in the system, either in the design phase or as strategic decisions and modifications to the system during the operation phase. Two distinct problems has been considered in the literature are 1) flexibility in the design process, and 2) flexibility as an attribute of the system in the face of unexpected changes. In the first case, (Saleh, Mark et al. 2009) make a distinction between flexibility in the design process and flexibility of the design itself.

#### 2.3.3.2 Flexibility in the Design Process

Various researchers have developed a large numbers of approaches to capture uncertainty in the early stages of design (i.e. before the system is fielded) and offers flexibility in specifying the design requirements. Designer's preferences with degrees of satisfaction in specifying design requirements have been incorporated in typical approaches. (Thurston 1991) presents a utility theory-based preference function to reflect the designer's preferences for sets of multiple attributes thus provide evaluation of design alternatives. (Wallace, Jakiela et al. 1996) propose a specification-based design evaluation method to emulate how specifications are used by product designers in concurrent design environment. (Chen and Yuan 1999) develop a probabilistic-based design approach to provide a range of solutions that satisfy a ranged set of design requirements. A design metric named Design Preference Index (DPI) is introduced to evaluate the goodness of a flexible design when both the design performance and the preference level of performance vary within the ranges.

Flexibility in the design process has been understood as an ability to balance between "the customer's ability and willingness to lower product expectations" and "the product developer's willingness and ability to invest more resources to reduce technical risks and other gaps before grogram start."(GAO-01-288 2001). While a slightly different understanding of flexibility in the design process is proposed by (Chen and Lewis 1999). Flexibility in design is achieved by finding solutions to satisfy a range of requirements between different teams of designers working on separate subsystems of a complex engineering design.

**Flexibility of a Design**

There is increasing recognition that flexibility is a key property of a design which not only allows system to mitigates downside risks but also capture upside opportunities.  An increasing number of researchers have attempted to provide clearly articulated and unambiguous definitions of flexibility in design, assess its value, and propose useful indications on how to embed flexibility in the design of products or systems and how to trade the value of flexibility against the penalties (cost, performance, risk, etc.) associated with it. The penalties of embedding flexibility or named switching costs can be monetary cost (real dollars), or quantifiable costs associated with personnel considerations, political implications, or the time to switch (Silver and de Weck 2007).

(Saleh, Hastings et al. 2003) define flexibility of a design 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." This definition distinguishes between requirements as capability, the ability for the system to "change its mode of operation", and attribute, the ability for the system to modify its performance. Several examples in long-term systems illustrate that flexibility in design is valuable due to its ability to accommodate changing environment and customer requirements. The authors quantify the value of flexibility in terms of design lifetime extension.

A variety of methods have been proposed to measure flexibility in different field. For example, in space systems, (Shaw, Miller et al. 1999) quantify flexibility in space systems by using adaptability metrics which measure "how flexibility a system is to changes in the requirements, component technologies, operational procedures or even the design mission."   Flexibility in space systems is denoted as type 2 adaptability which is defined “to be the proportional change in the CPF (Cost-per-Function) in response to a particular mission modification”,

$$F\big|_X = \frac{\Delta CPF}{CPF}\bigg|_X ,$$

where X is “just an identifier to specify the mission modification”. The CPF is “a measure of the average cost incurred to provide a satisfactory level of service to a single Origin-Destination pair within a defined market.” (Shaw, Miller et al. 2000) further define flexibility as the ease of movement from one design point to another on the tradespace design surface. Each point in this tradespace shows the architecture design variables vs. the associated CPF metric which describes the ‘ease’ of movement in the tradespace.

(Nilchiani, Joppin et al. 2005) explored the flexibility for an orbital transportation network (OTN). The authors focus on provider-side flexibility for on-orbit servicing within the context of orbital transportation networks. The total provider-side flexibility is calculated as the weighted sum of the three types of flexibility: mix flexibility, volume flexibility, and emergency service flexibility. Mix flexibility is described as the strategic ability to offer a variety of services with the given system architecture, quantified as

$$f_m = \frac{S_m - E_m}{S - E} ,$$

where $f_m$ is the mix flexibility, $E$ is the total system cost over, $S$ is the total revenue and $m$ denotes multiple types of services.

**Distinction between Process and Design Flexibility**

Both process flexibility and design flexibility, as defined earlier, refer to an ability to handle change. The major distinction is that process flexibility handles requirement changes occurring before fielding a system, while design flexibility handles requirement changes after fielding.

In current real options practices, flexibility can be embedded both in the initial design phase and operation phase through a sequence of strategic decisions to improve the system under the uncertain system environment.

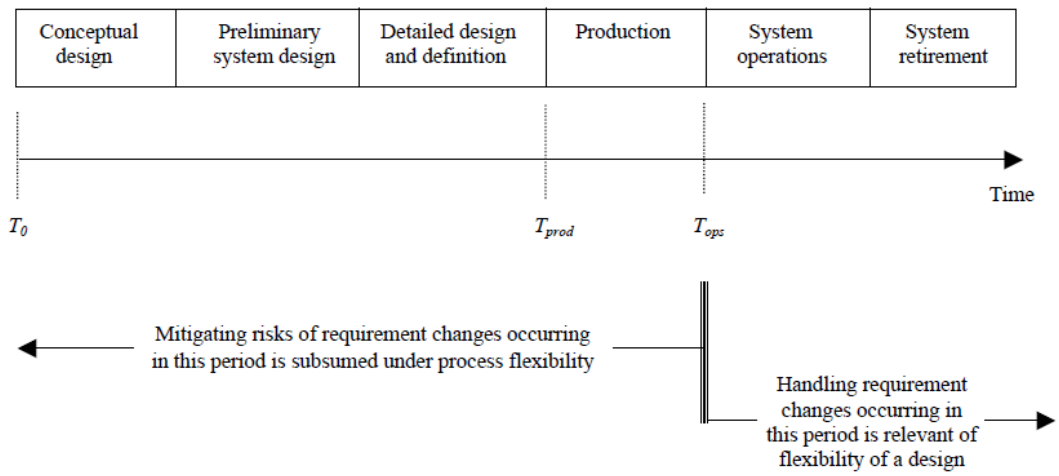



**Figure 2-1 Time frame attached to a system 's life cycle, and periods associated with process flexibility versus flexibility of a design (Saleh, Mark et al. 2009)**

### 2.3.3.3 Flexibility in decision theory

From a decision-theoretic perspective, flexibility can be viewed as an attribute of a decision problem and measured as the number of remaining alternatives to select after previous commitments are made. (Gupta and Rosenhead 1968) were the first to measure the flexibility of a decision in terms of "the number of end states which remain as open options" after a first decision is made. (Mandelbaum and Buzacott 1990) develop a framework for the treatment of flexibility in a two-period decision problem.

#### 2.3.3.4 Flexibility in Manufacturing Systems

The notion of flexibility has been wildly studied and applied in manufacturing systems, as discussed in (Browne, Dubois et al. 1984; Sethi and Sethi 1990; Gerwin 1993; De Toni and Tonchia 1998; Koste and Malhotra 1999; Bengtsson 2001). The literature is mainly focus on two aspects: 1) the definition and classification of different types of flexibility; 2) the development of flexibility measure and optimization algorithms for flexible manufacturing systems (FMS). In general, manufacturing flexibility is accepted as an ability to reconfigure manufacturing resources in order to effectively respond to changes in the system's environments with little penalty in time, effort, quality (Upton 1994). Thus based on the types of change the production system can accommodate, different types of flexibility are defined, such as volume flexibility, routing flexibility, expansion flexibility and product mix flexibility. Other classifications for different types of flexibility in manufacturing are also discussed in the literature. For example,(Narasimhan and Das 1999) distinguish the level of: 1) operational flexibility which refers to flexibility in machine and shop level; 2)tactical flexibility which refers to flexibility in plant level; 3)and strategic flexibility which refers to firm or business level. (Koste and Malhotra 1999) provide five hierarchical levels of different types of flexibility, from machine and material handing flexibility, to shop floor flexibility, plant level flexibility, and strategic business unit flexibility.

## 2.4 Flexibility and Real Options

Flexibility is often referred to as real options for several reasons. Firstly, "Real option thinking" views the future investment opportunities as options in non-financial or real assets where much of the option value arises from flexible decisions and learning over time. Secondly, this framing enables correctly measurement of the monetary value of a flexible system under uncertainty. Flexibility increases the value of engineering systems by limiting downside loss and taking advantage of upside opportunities. However, traditional valuation techniques such as DCF are unable to incorporate flexible decisions in the valuation procedures when new information obtained and uncertainty resolved over time, thus underestimating the value of a project or a system. In contrast, ROA applies dynamic modeling techniques (e.g. binomial lattices/trees, Monte Carlo simulation) to specify the asymmetrical distribution of possible outcomes with options.

## 2.4.1 Simple and Complex Real Options

Some real options occur naturally (e.g. by deferring, contracting, temporally shutting down or abandoning), while other can be created with extra cost:

(1) by staging large capital investments or large project into a sequences of stage;

(2) by introducing “modularity” in manufacturing and design;

(3) by investing in a platform-like initial infrastructure or design for potential future growth

(4) by developing new products or enhance system performance through R&D investment

(5) by investing in information acquisition

## 2.4.2 Real Options “on” or “in” Projects/Systems

Real options have been classified into two categories: real options “on” projects/systems and “in” projects/systems (Wang and de Neufville). For real options “on” projects, options are created by changing the scale and timing of capital investments, while treating the engineering design as a black box. Real options "in" projects, on the other way, are planned and embedded in engineering systems by altering the technical designs of large complex engineering projects and systems. To discover and exploit this type of options "in" systems, in-depth knowledge in technical and non-technical domain is required.

## 2.5 General Frameworks for Embedding Flexibility in Engineering Systems by Utilizing Real Options

Real options literature generally presents a three step-wise framework based on a well-known decision-making process developed by (Simon 1977) for building flexibility in engineering systems, as shown in Figure 2-2. The first step is framing, where decision makers define the target system and its objectives, identify and model uncertainties that impact the system performance or value. The second step is design, where decision makers create the alternative designs to provide flexibility in operation and physic structure. The final step is choice, where decision makers assess the value of alternative designs and select the optimal subset of designs. A variety of research work in real options literature generally follows this framework, such as (Zhao and Tseng 2003; Wang and de Neufville 2005; Zhang and Babovic 2011).

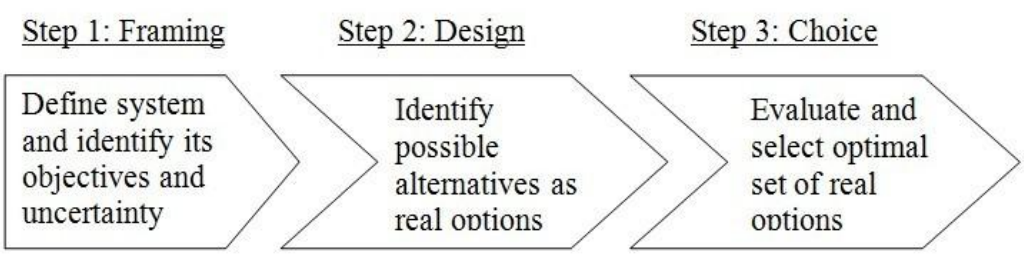



**Figure 2-2 General framework of real options analysis**

However, this simplified framework might have a limitation that readers might infer the design of flexibility as a front-end activity in physical domain rather than a lifecycle socio-technical interaction in physical and non-physical (e.g. human) aspects of the system. Since uncertainty inevitably occurs along the life time of system, more comprehensive frameworks are proposed to emphasize the lifecycle point of view, also to adapt to increasingly complexity of uncertainty and systems. Sussman defines engineering system as a “Complex, Large-Scale, Integrated, Open System (CLIOS)” and propose a three-phase framework for modeling the design and management process of complex socio-technical systems (Sussman 2000). Figure 2-3 describes the structure of CLIOS. The three main phases are: representation; design, evaluation and selection; and implementation. The aims of the presentation phase to fully understand the structure and behavior of the system, thus helping articulate the performance measures and system goals in the next phase. The second phase is the design and evaluation phase that generates the optimal design strategies for the best performance of the system under uncertainty. The last phase is the implementation phase, where the selected strategies are implemented in both physical and social system dimensions. By integrating and adding to the CLIOS modeling methodology, McConnell constructs a life-cycle flexibility framework for explicitly addressing flexibility/real options for uncertainty across the life time of complex systems (McConnell 2007). Figure 2-4 displays an overview of the life-cycle attribute of an option. A management loop is depicted for constantly managing monitoring and option exercise activities.

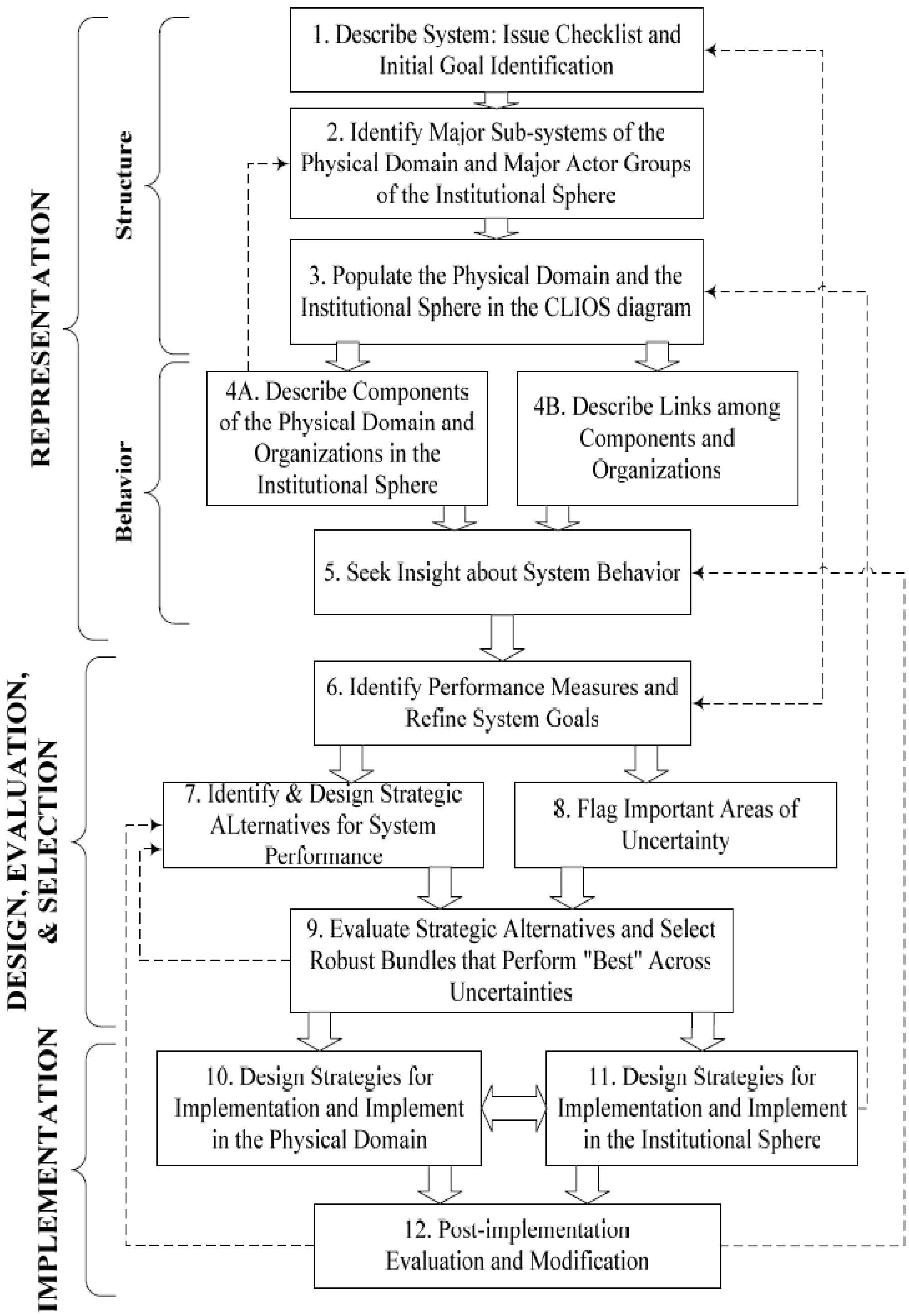



**Figure 2-3 CLOS framework (Sussman 2000)**

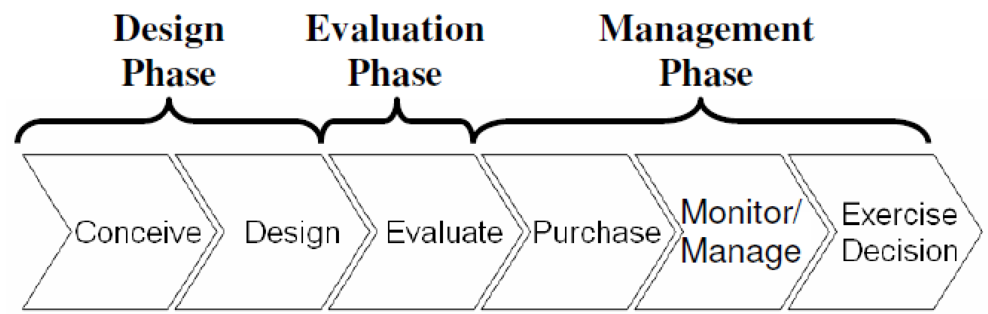



**Figure 2-4 Life-cycle of option (McConnell 2007)**

# 2.6 Approaches for Real Options Identification

## 2.6.1 Introduction

One of the key challenges for applying real options in complex engineering systems is to identify potential locations within the system to create options for flexibility (Shah, Viscito et al. 2008). The identification of real options "in" system designs requires insight into the physical and non-physical aspect of system, reorganization of relevant sources of uncertainties, and the ability to evaluate the dynamic behavior of the system. As the number of design variables grows and the interactions of system elements become more and more complex, the decision space for flexible designs increases greatly in size. It is even more challenging when facing multiple change scenarios through the lifetime of the system. This section classifies and discusses existing approaches for identifying flexible design opportunities "in" various complex systems. Currently, there are two broad classifications of analytical approaches for real options identification "in" lager engineering projects: direct and indirect interactions (screening) approaches. The direct interaction approaches utilizes various techniques developed in cognitive science, collaboration engineering and engineering design research, such as interviews, questionnaire, discussions and interactions, to help designers directly generate flexibility idea when considering uncertainties. The second categories of real option identification approaches are screening (indirect) approaches which require knowledge in both physical and non-physical domains of the system, insight into main sources of uncertainty and dynamic behavior of the system (Shah, Viscito et al. 2008). Depending on the fidelity and type of the model, a system element can be a subsystem, design variable, and a physical component, etc. Screening approaches can be further classified into screening approaches and matrix-based approaches.

## 2.6.2 Direct Interaction Approaches

One intuitive way to identify the real options is through interviews of subjective matter experts (SMEs) and system stakeholders (Cardin and De Neufville 2008). The direct discussion and interaction with designers guide the designers to think about what types of changes to the system are likely to occur and potential areas to incorporate flexibility in response of such changes by their intuitions and experiences, without requiring explicit identifications and analysis of system components first. These approaches are usually referred to as direct interaction approaches. Without investigating details in system representation, these approaches rely on designers' insights and experience in their own specific domains and provide high-level, low-fidelity perspective on real options "in" engineering projects and complex systems. They can help identify real options which are both agreed by the system owner and operators and are particularly effective for a limited number of change scenarios and simple systems where there is no need to consider change spreading between system components. However, currently the direct interaction approaches are still not well established and require to limit the biases carefully (Cardin, Kolfschoten et al. 2012).

## 2.6.3 Screening Approaches

Effective screening models are required to reduce the number of alternatives to be examined in detail for further intensive capital investment. They are used as an effective tool for exploring and identifying potential flexible design opportunities and have been exploited in system design and analysis for a long time. Preliminary screening models are proposed by (Jacoby and Loucks 1972) in water resource planning problems. Optimization and simulation techniques were applied for selecting alternative design configurations of reservoir systems. More applications of screening models in this area can be found in (Chaturvedi and Srivastava 1981), (Stedinger, Sule et al. 1983), (Srivastava and Patel 1992; Millspaugh 2010).

In the screening process, analysis of complex engineering systems often starts with simplification of physical reality according to knowledge about a system and research purposes. Based on simplified representation methods adopted to describe and analyze engineering systems, screening models can be broadly classified into two major categories: mathematical equation-based and matrix-based screening models. The following reviews previous work on screening models and approaches for flexible opportunities identification in the engineering design process.

## 2.6.4 Mathematical Equation-based Screening Approaches

The first category of screening models is mathematical equations based. Mathematical equations are used to describe objective functions and constraints of design problems, and then screening models are developed to identify essential design parameters of physical systems and explore flexible strategies under uncertainties. Global optimization techniques are often used to screen out such design candidates. For example, Zhao (2003) proposed a multistage stochastic optimization model to select design alternatives for high way development according to different initial conditions. Wang (2005) developed a deterministic mix-integer optimization programming model to identify optimal initial configuration of design parameters for the river basin development. In his screening model, the problem is simplified by using low-fidelity cost functions, reducing time periods and limiting numbers of possible scenarios. Zhang (2008) presented an evolutionary real options framework for searching the optimal initial design and a portfolio of real options with their exercising conditions along different paths in a trinomial scenario tree.

Although the above screening models are able to provide optimal and accurate results after some simplification, the computational complexity will pose a significant challenge for traditional optimization approaches with the expansion of decision spaces. To address this issue, some other mathematic equation based models have been developed to screen out a small group of design candidates which are most valuable for detailed design phase in the large decision spaces with less computational effort. Lin (2008) developed an analytical screening model with several design rules which integrate physical systems, project development and economics to explore flexible strategies in offshore oilfield production systems. Yang (2009) presented an adaptive searching model which combines Design of Experiments (DOE) methods (i.e. adaptive one-factor-at-a-time and response surface methodology) with traditional optimization method (i.e. simulation-based linear programming) to explore planning decisions in automotive manufacturing systems under demand uncertainty. These models are able to rapidly search huge decision spaces and provide approximate results which are adequate in the early design phase.

However, mathematical equations-based screening models are generally suitable for problems with limited numbers of design parameters and limited interactions between them. These models do not take the structure and connectivity of system components into account. In reality, many complex large-scale engineering systems are composed of a large number of components. It is of great importance to consider the interdependence between these components in complex and large-scale engineering system design problems.

## 2.6.5 Matrix-based Screening Approaches

### 2.6.5.1 System Representation by Matrix-based Models

As the second category of screening models, matrix-based approaches are applied for system modeling and analysis. The commonly used matrix-based models in system engineering and project management are design (also called dependency) structure matrix (DSM), domain mapping matrix (DMM), and multiple-domain matrix (MDM). The last two matrices are the enhancements of DSMs. These models are widely used in systems engineering and project managements to provide a concise visualization for the structures of complex systems and product development processes (Browning 2001).

**Design Structure Matrix**

First invented by Steward (Steward 1981), DSM is a simple, compact and visual representation and analysis tool and is widely applied in both research and industrial practice, even though some of the DSM methods (e.g. partitioning and tearing) has been in use since the 1960s.

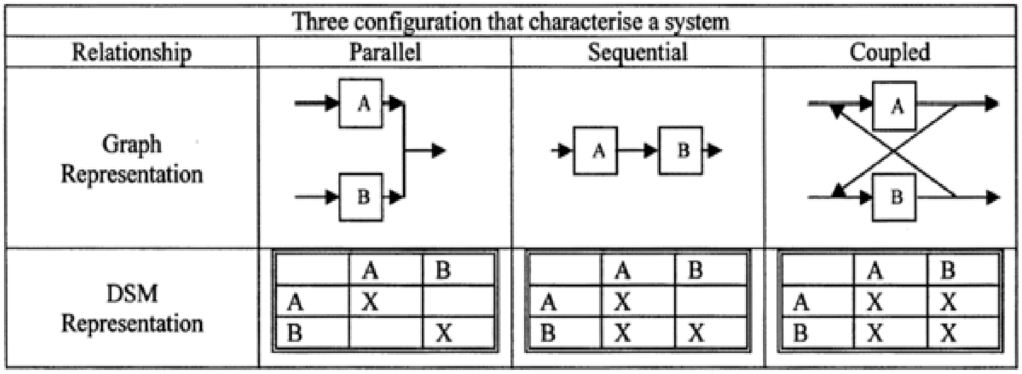



**Figure 2-5 the DSM representation and the associated directed graph**

A DSM is a square matrix with identical row and column labels. Each row (and the respective column) label corresponds to a system element (e.g. a sub-system, process, task or system component). The DSM is a matrix representation of a directed graph. Figure 2-5 shows three configurations that characterize a system by DSM representation and directed graph representation. The value or mark in the off-diagonal entries of the matrix body depicts the relationships between the column and the row elements. For instance, if there is a directed arc from node $A$ to node $B$, then the entry value in column $A$ and row $B$ is marked with "X" or "1".

According to the types of the system elements, a DSM can represent the relationships among components of an engineering system, teams for organizational design, activities of a design process and parameters for an activity or a process (Browning 2001).

Typically, DSMs are intra-domain matrices which represent the system elements only within a single domain. For example, only components and their relations are modeled in a DSM. Analytical methods available for common DSMs, like partitioning and tearing, do not capture the system interactions with the environments.

## Domain Mapping Matrix

Extending from DSM methodology, a domain-mapping matrix (DMM) is an inter-domain matrix which links elements in two different domains. Developed by Danilovic and Browning, the DMM uses rectangular matrix to relate two DSMs in different domains: the rows represent elements in one domain, while the columns represent elements in another domain (Danilovic and Browning 2007). The authors mainly focus on product development projects and present studies on linkages between five important project systems/domains: "the goals domain of the product (or service, or result) system; the process system (and the work done to get the product system); the system organizing the people into departments, teams, groups, etc.; the system of tools, information technology solutions, and equipment they use to do the works; and the system of goals, objectives, requirements, and constraints pertaining to all systems."

## Multiple-domain Matrix

Multiple-domain matrices (MDM) or multiple design structure matrices are the combination of DSMs and DMMs. Figure 2-6 shows an example of MDM which consists of elements groups in different domains and a symmetric alignment of elements on both row and column heads. The DSMs align along the MDM diagonal, and the DMMs align in the upper and lower triangular.

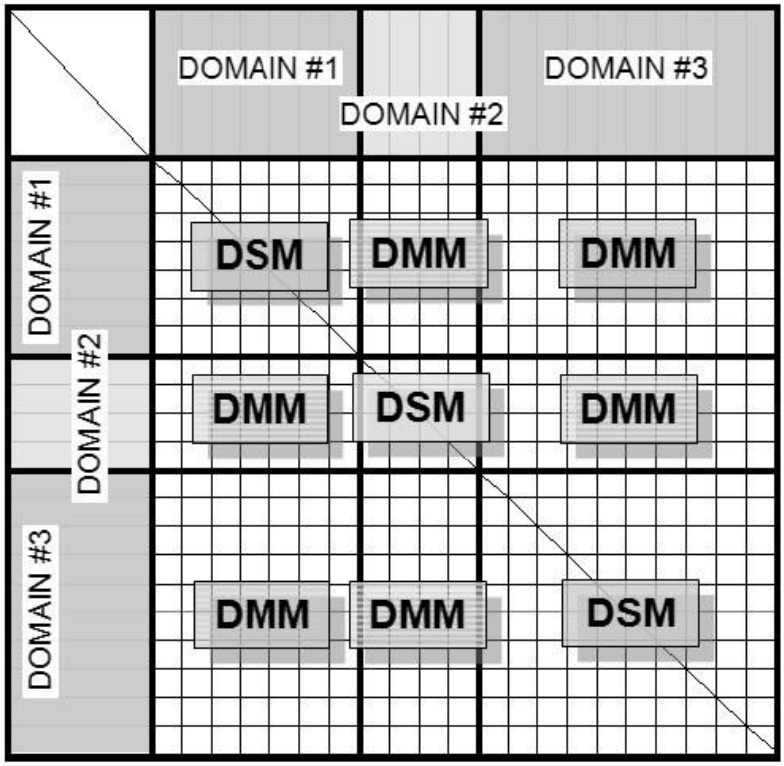



**Figure 2-6 An example MDM (Eichinger, Maurer et al. 2006)**

Eichinger et al. (2006) identify five domains (i.e. components, functions, parameters, resources and tasks) for constructing MDM for product developments, and propose an analysis process to determine the indirect relations between elements using data stored in the matrices.

**Engineering System Matrix (ESM)**

Similar to MDM, Bartolomei (2007) developed the engineering system matrix (ESM) to include multiple aspects, multiple relations and changes over time for engineering system representation. Figure 2-7 displays an ESM representation of an engineering system composed of technical, social and environmental aspects. The ESM methodology specifies an engineering system in six interrelated domains: environmental or system driver, social or stakeholders, functional including objectives and functions, physical or objects, and process or activities. System drivers represent non-human components that are beyond stakeholders' control, like social, political, economic and technical system influences. Stakeholders represent individuals or organizations that affect or are affect by the system. Objectives represent the objectives, goals and purposes of the system. Functions represent the functions or functional requirements of the system. Objects represent physical components of the system. Activities represent the processes, sub-processes, and tasks that are performed for the system objectives accomplishment. Parameters represent the system parameters for the internal stakeholders, objects, and activities. The ESM can be constructed by using extensive document review and interview approaches. Bartolomei (2007) provides detailed insights and elaborates a nine-step guide to create an ESM.

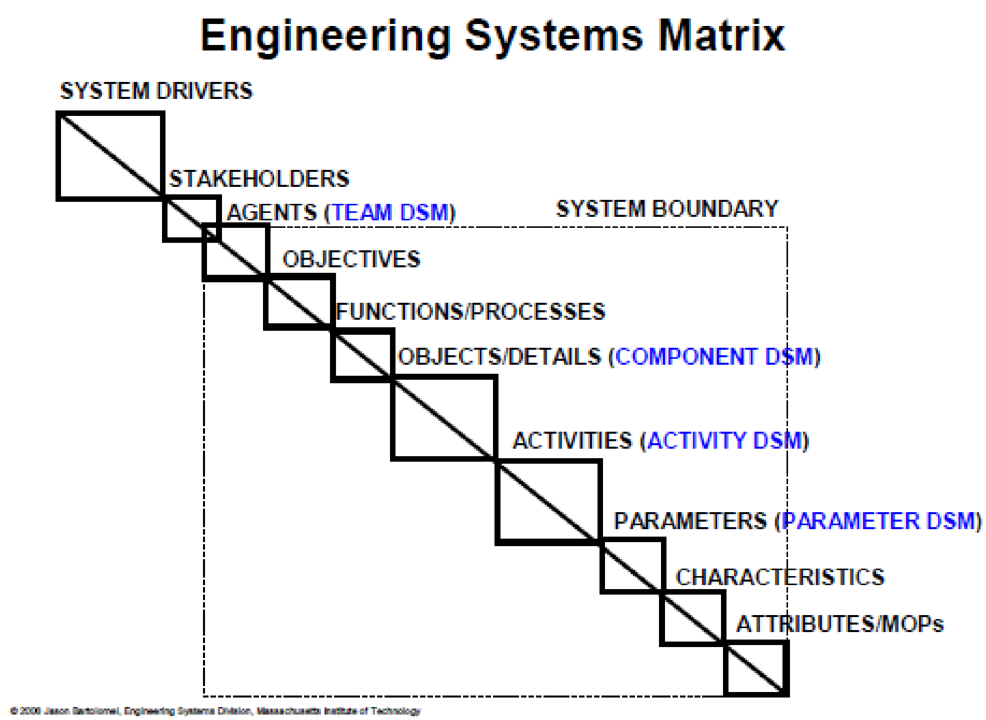



**Figure 2-7 The ESM representation of an engineering system composed of technical, social and environmental aspects (Bartolomei, Hastings et al. 2006)**

According to design purposes, requirements and available information during each stage of the design process, designers can construct and specify the ESM with appropriate complexities and levels of abstraction. With the growing numbers of system elements and the increasing connectedness of them, the complexity of the ESM will also increase in size and density. However, by dividing a large, complex ESM into sub-matrices, with DSMs aligning along the diagonal and DMMs off-diagonal, the designers can focus on subset of domains according to their specific design problems, such as system driver domain and physical components domain. In addition, different levels of abstraction on system elements in different domains of the ESM are determined based on available information and the designers' experiences. In the early design conceptual stage, the information regarding specific physical components may be unavailable, thus the designers can only construct higher level of abstraction, like sub-systems. Since the focus of this screening approach is the physical area in the early conceptual stage, the required ESM is constructed with high-level abstractions (e.g. sub-systems). Yet the resulting analysis for flexibility opportunities identification can be applied in all levels abstraction of the ESM.

Additional information is stored in the ESM to provide comprehensive system representation. For instance, components and relations in the ESM can be described with attributes which define the characteristics for each particular components or relations. These attributes may include specific numeric values, mathematical equations, relationship types (e.g. material, information, spatial and energy relations).

#### 2.6.5.2 Change Propagation Analysis

To identify important system elements (e.g. sub-systems, physical components) for flexibility, the system behaviours in response to external change should be analysed. How a particular system or system element responds to change dependent on its potential ability to absorb and generate, which is determined by its change margins and the functional reaction to change. By examining the degree of change a system or system element can absorb and the degree of change it deliver, (Eckert, Clarkson et al. 2004) identify four types of change behaviours:

1. Constants are “unaffected by change.” They do not generate change by themselves or absorb other changes.
2. Absorbers can absorb more change than they themselves generate.
3. Carriers “absorb a similar number of changes to those that they cause themselves”
4. Multipliers “generate more changes then they absorb.”

It should be note that the change behavior of an element depends on both the scale and nature of the change and also the state of the design. An element may be an absorber under small change, but which it is affected by a large change, it may become a carrier or even worse a multiplier. Therefore, not only the direction of change spread in the system but also the scale of change should also be taken into account in change propagation analysis.

#### 2.6.5.3 Change Prediction Method

Predicting change propagation is not straightforward. Due to the connectivity of system elements, a change in one element is more likely to trigger changes in other elements, which in turn may propagate to more elements. Direct change occurs when change in one element cause change in another element without going through a third element (Clarkson, Simons et al. 2001). Indirect change occurs when change in one element trigger change in another element indirectly, by going through other element(s). Indirect change further increases the complexity of the analysis.

Change prediction method (CPM) developed by (Clarkson, Simons et al. 2001) computes the risk of change propagation between system elements. This method follows three stages: system representation, change prediction, and change management. In the first stage, system elements and the connectivity between them are modeled by a change propagation network and represented by a binary DSM. The scale of change is measured as a probabilistic cost or risk, which is the product of the likelihood and impact of the change occurring. By replacing the entries of the binary DSM with values between 0 and 1, direct likelihood DSM and direct impact DSM are generated and combined to represent the direct risk of change relationships between system elements. In the second stage, the combined risk of a particular change in one element propagating to its direct and indirect elements is calculated by a numerical searching-based algorithm, termed Forward CPM (Hamraz, Caldwell et al. 2012). The numerical algorithm views the change propagation of from an initial an element $E_I$ to a specific affected element $E_A$ as a logic tree. The tree is formed by searching all the possible paths that could be followed from $E_I$ to $E_A$. This searching manner is called a *brute-force search* or *exhaustive search*. Combined likelihood and risk value are calculated along the tree through a combination of *And* and *Or* evaluations, where *And* represents intersection operation in the joint of two vertical paths and *Or* represents union operation in the joint of a number of horizontal paths. Figure 2-8 depicts an example logic tree and the equation for computing the combined likelihood of change propagation from node $a$ to node $b$ .In the third stage, the combined risk matrix is used for change mitigation or exploration in complex engineering system and human activities management.

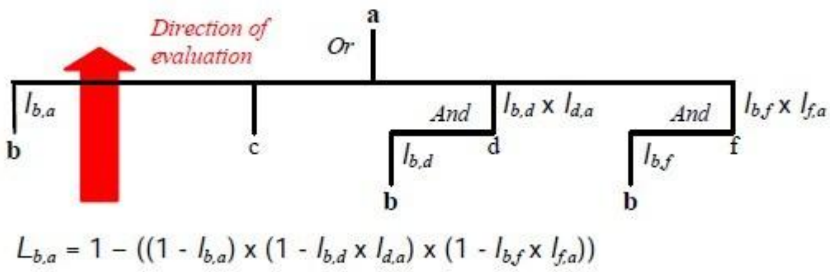



**Figure 2-8 And/Or summation for a propagation tree**

#### 2.6.5.4 Identify Critical Elements for Flexibility

Based on CPA, Suh et al. (2007) presented a flexible platform design framework to identify critical platform components for build-in options. The authors introduce a metric, Change Propagation Index (CPI) to measure the degree of change propagating through a system element by the difference between its change flows in and out. The change inflow and outflow of an element are quantified by the number of incoming and outgoing edges of that element as shown in Figure 2-9.The elements which multiply or carry changes in a system are identified as potential candidates for flexible design. However, the CPI is calculated by only counting the numbers of direct change inflow and outflow of a system element. The scale of change is taken into account after the identification of critical elements for flexibility. An element may be affected by a number of changes, if all these changes are minute, it may remain unchanged. Moreover, the indirect change interactions are not considered in the CPI calculation.

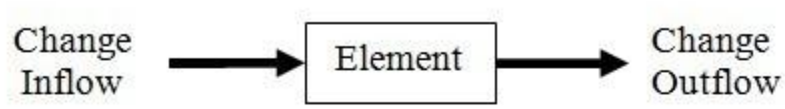



**Figure 2-9 Change inflow and outflow of a system element**

Instead of identifying potential area to incorporate flexibility directly, Kalligeros (2006) developed a methodology to identify a platform as collection of invariant components according to Design Rules (Baldwin & Clark 2000). The methodology is based on the extended sensitivity-DSM (Yassine and Falkenburg, 1999) to model the changes of system components due to the external effects, and an algorithm is developed to identify the platform components as they are directly unaffected by any other components and all external functional requirements.

Bartolomei (2007) proposes a nine-step process which incorporates and extends the Kalligeros and Suh's work by using ESM to identify system "hotspots". A system hotspot is a system component which is very to be desired to change and has a high switch cost associated with the change, or has a low switch cost associate with the change yet high perceived benefit to the system performance. Bartolomei demonstrates the proposed approach through experiment of the hotspot identification in Micro Air Vehicle platform. No formal sensitivity analysis and change propagation analysis was conducted.

# 2.7 Approaches for Real Options Valuation

Since real option theory is derived from financial option theory (Black and Scholes 1973; Myers 1977), this section first introduces financial option and option pricing methods, followed by real options.

## 2.7.1 Option Pricing

In finance, an option is a contract which gives the owner the right, but not the obligation to buy or sell an underling asset (e.g. stocks, stock indices, foreign currencies, commodities, futures contracts and debt instruments) at a predetermined strike price on or before a specified date. The cost to obtain an option is the option price. An underlying asset is the asset on which the price of a derivative such as option depends, such as stocks, stock indices, foreign currencies, commodities, futures contracts and debt instruments.

There are two basic types of options: calls and puts. A call (put) option provides the holder with the right to buy (sell) a specified quantity of an underlying asset at a fixed price (called a strike price or an exercise price) at or before the expiration date of the option. Financial options are also categorized by the time when they can be exercised. American options can be exercised at any time prior to its expiration, while European options can be exercised only at expiration.

#### 2.7.1.1 Modeling Uncertainty

Mathematically, it is assumed that the value of an underlying asset follows the same stochastic process of stock price in financial option theory: a geometric Brownian motion (GBM) process (illustrated in Figure 2-10).

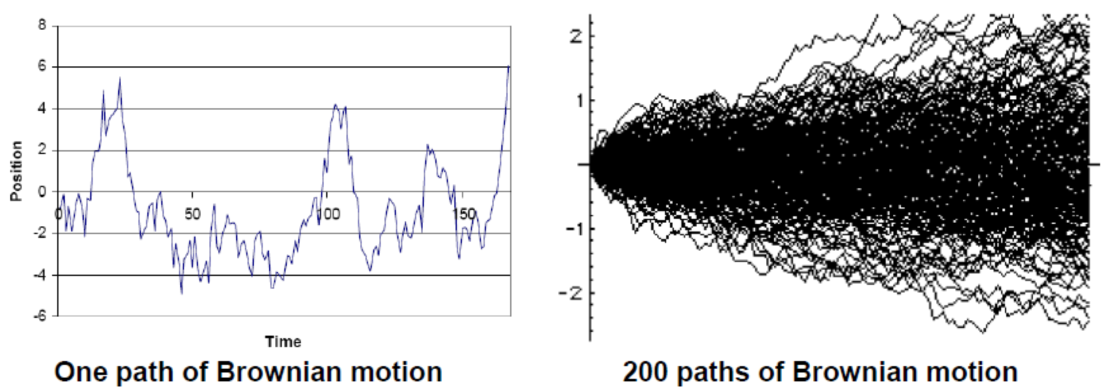



**Figure 2-10 Brownian motion (source: www.wikipedia.org)**

A stochastic process of a stock price $S_t$ is said to follow a GBM if it satisfied the following stochastic differential equation (SDE):

$$dS_t = \mu S_t dt + \sigma S_t dW_t \tag{2.1}$$

$$dW_t = \varepsilon\sqrt{t} \tag{2.2}$$

where $S_t$ is the value at time $t$ , $dt$ is the time step, $\mu$ is the drift, $\sigma$ is the volatility, $W_t$ is a standard Weiner process or Brownian motion, and $\varepsilon$ is a normal distribution with a mean of 0 and standard deviation of 1. Both of $\mu$ and $\sigma$ are constant. Using Ito's lemma[1]:

$$d\ln S_t = (\mu - \frac{\sigma^2}{2})dt + \sigma dW_t \tag{2.3}$$

From this equation, the change in $\ln S$ between 0 and $t$ is normally distributed, so that $S$ follows a lognormal distribution. The discrete-time expression for the lognormal distribution of S is:

$$S_{t+\Delta t} = S_t e^{(\mu - \frac{\sigma^2}{2})\Delta t + \sigma\varepsilon\sqrt{\Delta t}} \tag{2.4}$$

Equation (2.4) indicates that the volatility of a stock price $S_{t+\Delta t}$ at time $t + \Delta t$ is the standard deviation of the return provided the stock price $S_t$ at time $t$, and the return is expressed using continuous compounding.

### 2.7.1.2 Standard Option Pricing Techniques

The value of an option can be calculated by a variety of quantitative techniques based on two assumptions: GBM of the underlying asset and no arbitrage. The first assumption is discussed in previous section. Arbitrage refers to the simultaneous purchase and sale in different markets to achieve a certain profit. In

[1]Ito's lemma states that if the value of a variable x follows an Ito process of the form, $dx = a(x,t)dt + b(x,t)\,\mathrm{d}W$ where $W$ is a Wiener process, then any smooth function $G(x,t)$ follows the process, $dG(\frac{\partial G}{\partial x}a + \frac{\partial G}{\partial t} + \frac{1}{2}\frac{\partial^2 G}{\partial x^2}b^2)dt + \frac{\partial G}{\partial x}bdW$ where $dW$ is the same Wiener process. Thus, G also follows an Ito process.

market equilibrium, there must be no opportunity for profitable arbitrage. Otherwise one could make a certain profit by buying low (buying the undervalued asset) and selling high (selling the overvalued asset). There would be excess demand for the former and excess supply for the latter. The no arbitrage assumption is used in quantitative finance to calculate a unique risk-neutral price for an option.

In general, the value of an option is determined by the following variables relating to the underlying asset and financial (Damodaran 2005):

1. Current Value of the Underlying Asset $S_0$
2. Strike Price of Option $X$
3. Time to Expiration on Option $T$
4. Risk-Free Interest Rate $r_f$
5. Uncertainty (with Volatility as the Measurement) in Value of the Underlying Asset $\sigma$

According to the paradigm used to represent the evolution in time of the model's input variables, standard valuation techniques can be classified into two types: continuous- and discrete- time (Perlitz, Peske et al. 1999). In continuous-time approaches, closed-form equations, stochastic differential equations and Monte Carlo simulation are utilized. Multinomial lattices/trees are commonly used in discrete-time approaches.

**Black-Scholes Model**

Black-Scholes (B-S) model is one of the foundations for existing financial market (Black and Scholes 1973). It provides a close-form formula for valuing the prices of a European option on a non-dividend paying stock at time zero by constructing a risk neutral portfolio that replicates the returns of holding an option. The value of a European call option is calculated as

$$C = S_0 N(d_1) - Xe^{-r_f T} N(d_2) \tag{2.5}$$

Where, $d_1 = \dfrac{\ln(S_0 / X) + (r_f + \sigma^2 / 2)T}{\sigma\sqrt{T}}$;

$$d_2 = \frac{\ln(S_0 / X) + (r_f - \sigma^2 / 2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T} .$$

and $N(x)$ is the cumulative probability distribution function for a variable that that is normally distributed with a mean of zero and a standard deviation of 1.0.

The B-S model is elegant and relatively simplistic to use so it requires almost no computation time or resources. However, one major limitation of the Black-Scholes model is that it cannot be used to accurately price options with an American-style exercise as it only calculates the option price at one point in time – at expiration. It does not consider the steps along the way where there could be the possibility of early exercise of an American option.

**Stochastic Differential Equations**

Stochastic differential equations are continuous-time approaches which solve the partial differential equation (PDE) for option modeling. A number of numerical finite difference methods exist for desired option. While the numerical method is mathematically intensive thus is difficult to use by most practitioners without strong mathematical background.

**Monte Carlo Simulation**

Monte Carlo simulation (MCS) uses a simulation technique to randomly generate possible price paths of the underlying asset to simulate payoffs for the option which are then discounted at the risk-free rate. A distribution of the results is obtained and these results are averaged to calculate the expected value of the option. One of the strong points of MCS model is that it requires only a predefined stochastic process of the underlying asset, and does not have any limitation on the number of assumptions on the options to be evaluated, thus it can be used for different models with varying assumptions (e.g. model for valuing multiple underlying assets, model with changing parameters). Despite its flexibility related to assumptions, a MCS model can be computationally intensive depending on the number of assumptions which must be built into the model. Also, it is more complicate for MCS to calculate American styled options and compound options than for discrete-time model (e.g. lattice and tree based model).

**Binomial Lattice/Tree**

Binomial lattice/tree model is one of the most popular approaches for discrete time approximation for the value of the underlying asset and option. The original binomial lattices for option pricing is developed by Cox et al. (Cox, Ross et al. 1979). It discretizes the GBM as a random walk. A random walk represents the price movement of the underlying asset as binomial for a number of discrete time intervals over the option's life. In comparison to the use of an abstract value $\sigma$ to describe volatility, in B-S formula, the binomial model starts with binomial lattices to represent the stochastic movements of the underlying asset: up or down by a specified amount. By constructing a riskless portfolio to replicate the option payoff, a simple formula can be used to calculate the option price at each node in the lattice/tree. This technique is illustrated in a two-step binomial lattice, where a two-branch tree structure of a lattice traces the evolution of the underlying asset value $S_0$, as well as option payoffs $f_u$ and $f_d$ (Figure 2-11). In the binomial tree, the up factor $u$, down factor $d$, and associated probability are calculated as follow:

$$
\begin{aligned}
u &= e^{\sigma\sqrt{\Delta t}} \\
d &= 1/u \\
p_u &= \frac{e^{r\Delta t} - d}{u - d} \\
p_d &= 1 - p_u
\end{aligned}
\tag{2.6}
$$

The valuation process works backwards, form each final node of the lattice (at option expiration date) to the first node (at valuation date). The value at the first node is the value of the option.

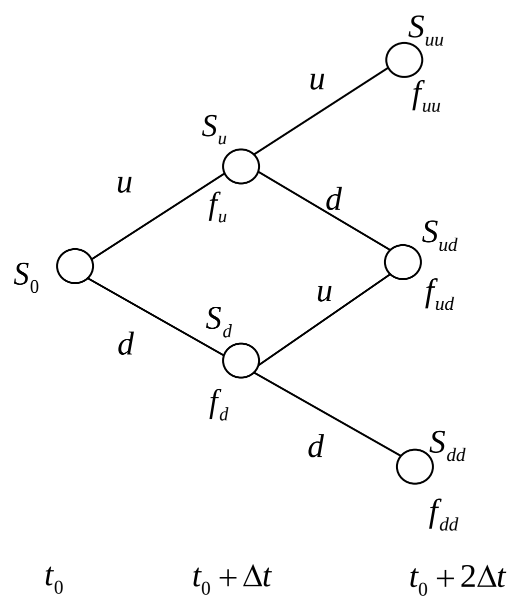



**Figure 2-11 A two-step binomial lattice**

The discrete-time models (e.g. binomial lattice/tree) and their continuous-time counterparts (e.g. B-S model) are based on the same assumptions and portfolios replicating mechanisms. Theoretically, a binomial lattice method can approximate the value calculated by B-S model to the desired degree of precision. A binomial lattice model is considered more flexible than B-S model for several reasons. For instance, a binomial lattice can model the discrete future dividend payments at any time steps, and it can also model the early exercise of an option. However, there are also limitations of a binomial lattice model. First of all, it is usually applied for only one source of uncertainty and constant parameters, thus is difficult to calculate option value with multiple underlying assets and non-constant parameters. Secondly, it is path independent which means that the payoff at each node is only determined by its state, not by the path it used to arrive at that node. To break path-independence, a binomial tree model can be used to provide separated chance node for each path, and its valuation method is the same as a binomial lattice one.

## 2.7.2 Real Options Valuation (ROV)

First coined by Stewart Myers (Myers 1977), a real option is defined as "the right, but not an obligation to take some action at a certain cost within or at a specific time period" (Trigeorgis 1996; Amram and Kulatilaka 1999; Schwartz and Trigeorgis 2001). Amram and Kulatilaka claim: "Options are valuable when there is uncertainty. Many strategic investments create subsequent opportunities that may be taken, and so the investments opportunity can be viewed as a stream of cash flow plus a set of options". Shortly, the management's ability to react to uncertainties in many non-financial assets and liabilities can been viewed as a collection of such options, which are commonly called "real options".

### 2.7.2.1 Key Input Parameters for ROV

The similarity of financial option and the option to alter decisions in a later time period opens the doors to build up the ROV technique. Both of them are exercised after the uncertainties are resolved. Early work on real options valuation demonstrates that if the analogous parameters in real options model can be appropriately estimated, any method used to value the financial options can be applied in the ROV. The classical approaches on early ROV literature are prominently relied on standard option pricing techniques and the associated assumptions behind them (Brennan and Schwartz 1985; McDonald and Siegel 1986; Dixit, Pindyck et al. 1994; Trigeorgis 1996; Amram, Kulatilaka et al. 1999). Leslie and Michaels (1997) examine the parameters in the Black-Scholes models and their analogies in the context of the real options framework. These relationships are summarized in Table 2-1.

**Table 2-1 Analogous parameters in financial and real options models**

| **B-S parameter** | **ROV parameter** | **Example Sources of Uncertainty** |
|---|---|---|
| Stock price, S | Present value of the real investment project | Market demand for products and services, labor supply and cost, materials supply and cost. |
| Stock price volatility $\sigma$ | Volatility of underlying cash flows | Volatility in market demand, labor cost, materials cost correlation of model assumptions |
| Exercise price, X | Present value of required investment costs in real asset | Availability, timing and price of real assets to be purchased |
| Time to expiration, T | Time period when the investment opportunity is alive | Product life cycle, competitive advantage |
| Dividend rate,$\delta$ | Chas flow lost to competitors | Convenience yield |
| Risk-free interest rate, $r_f$ | Risk-free interest rate | Inflation, money market behavior |

Comparing with financial option, it is more complicate to quantify such parameters for non-financial or real investment.

**Value of the Underlying Asset**

The value of the underlying asset in classical ROA approaches can be obtained by the assumptions that the real asset is traded in the market, or other traded assets can perfectly span the risk of the real asset, thus the value of the real investment project can be known from financial market. Unfortunately, most present value of underlying assets are not so straight-forward. In reality, for most projects with flexibility are not traded in capital markets, and other assets may (at best) partially span risk. For example, real assets such as a new product new technology in the research and development (R&D) projects are not being traded in the current markets. It might be hard or even impossible to find appropriate marketed securities, such as futures and stocks, to replicate the value movement of the real assets.

**Volatility**

Estimating an “accurate” volatility of stochastic process of the underlying asset is an important issue since it influences the option value. However, it is probably the most difficult input parameter to estimate in ROA (Mun 2006). For financial options the volatility can be estimated by observing the historical data of return distribution or calculating from traded option prices. However, it is difficult to quantify the volatility for many real options since neither historical return distribution nor traded option prices available. In addition, volatility for ROA is often determined by multiple sources of uncertainty. Three approaches are suggested for modeling volatility: twin security information, Monte Carlo simulation and educated estimates ((Luehrman 1998). Monte Carlo simulation is more widely used than the other two approaches since it does not require particular assumption except for the distribution of input variables. Copeland and Antikarov propose a standard process for estimating and aggregating volatility (Copeland and Antikarov 2001). In the simulation process, the distribution and correlations of multiple sources of uncertainty correlated to project cash flows are entered as input variables. After a number of simulation runs, an estimated underlying asset value and volatility are obtained by discounting the future cash values in a pre-determined discount rate. However, Smith points out that the volatility estimated in this approach is overestimated (Smith 2005). This is because that theoretically the volatility of the project's NPV is assumed to be constant and equal to the volatility of all cash flows in each time period, while during the simulation, the NPV of the project is calculated as the summation of all future cash flows which are generated in the simulation, and thus the calculated volatility is the combination of all future uncertainties. Brandão et al. suggests a modification to the specification of the volatility in Copeland & Antikarov simulation model. The volatility of the project value is only related to the stochastic cash flow $C_1$ in the first year, while cash flows in the following years are expressed as expected values conditional on the outcomes of $C_1$.

**The Exercise Price and Exercise Date**

For a ROA can be much difficult to estimate due to the reason that a real asset's exercise price may change over time or be lumpy, and the exercise date may dependent on the exercise of another real option or dependent on the resolution of some uncertainty.

**Interest Rate**

The risk-free interest rate is used in classical real option approaches. However, in many real option problems some risk characteristics (private risk, as opposed to systematic risk) cannot be replicated by trading in marketed securities, which means the markets are incomplete. It would be questionable to use the risk-free rate for all discounting since the risk-free rate is supposed to be free of private risk.

**Dividends**

Dividends in ROA are considered as a leakage in value (e.g. cash payouts, insurance fees, rental income) by Amram and Kulatilaka (Amram, Kulatilaka et al. 1999). While dividends of financial options are known in advance or can be quantified as a continuous payment over the option's life, for real options, the amount and timing of the dividends may be unknown or dependent on exogenous uncertainty in project or market. Brandão et al. (BDH) estimate dividend of a project as a cash flow payout rate which is constant across all states for each period but variable in time and is a fixed proportion of the value of the project in that period (Brandão, Dyer et al. 2005).

#### *2.7.2.2* Classifications of Project Uncertainties and Market Conditions

Unlike financial options which are only related to market-related uncertainties, options in non-financial or real assets are exposed to enormous uncertainties. In general, project uncertainties are divided into two parts: systematic (market-related) uncertainties and project-specific uncertainties (Smith and Nau 1995; Borison 2005). Systematic uncertainties are perfectly positively correlated with market, thus can be tracked or hedged by traded securities (e.g. fund, stocks) in the capital markets. However, some uncertainties in new technology and product development projects may or may not be correlated with the economy as a whole, thus they may not be replicable with a portfolio of traded securities (Borison 2005). These risk factors are project-specific. For example, a new drug development project for a pharmaceutical company may include risks that cannot be perfectly replicated by a traded asset, but the price of the product is clearly a "market risk".

With systematic risks along, market become complete: all the risks can be perfectly hedged by trading securities. The value of a project with systematic risks only can be valued by a straightforward application of standard option pricing techniques. However, many engineering projects and systems inevitably face a partially complete market condition where their uncertainties can only be partially hedged by trading securities (Smith and McCardle 1998). For most real asset investments where project-specific uncertainties are inherent, there is as yet no fully developed sound theoretical framework for real option pricing.

#### 2.7.2.3 ROV in Practice

The valuation approaches and associated assumptions which fit well for financial options are not necessarily suitable for real investments (Borison 2005; Triantis 2005). To bridge the gap between theory and practice, more valuation approaches have been proposed. In the financial literature, ROV approaches can be generally summarized into five categories: the classical, the subjective, the MAD, the revised classical, and the integrated approach (Borison 2005; Copeland and Antikarov 2005). It has been widely pointed out that classic and subjective approach are impractical for valuing projects with project-specific uncertainties (Smith and McCardle 1998; Borison 2005; Mattar and Cheah 2006). In this section, the MAD, the revised classical and the integrated approach which are able to deal with more realistic and complex valuation situations are examined.

MAD approach, proposed by Copeland and Antikarov (2001) is a approach named as which assumes that the best estimate of the market value of the project is the present value of the project itself, without flexibility. This assumption is known as market asset disclaimer (MAD). The MAD approach utilizes a binomial lattice to model the stochastic process of project value and can be applied to problems in cases where there is no market-traded asset. Under the MAD assumption, the value of the project without options serves as the underlying asset in the replicating portfolio, which implies that the markets are complete for the project with options. If the changes in the value of the project without options are then assumed to follow a lognormal distribution, geometric Brownian motion (GBM), then the options can be valued with traditional option pricing methods.

Another central assumption is that the firm is considered to be risk-neutral towards private risk. Therefore, the private risks are factored in relatively to their base case and their outcomes are discounted with the risk-free rate. Brandao et al. apply the MAD assumption and propose a binomial decision tree structure to approximate the GBM of the project value instead of the binomial lattice used in MAD approach (Brandão, Dyer et al. 2005). The authors suggest that modeling the evolution of project value and payoffs within the decision tree framework is more intuitive for practitioners and can be implemented using off-the-shelf decision analysis software. However, Smith comments on this approach and shows either tree or lattice yield similar numerical result if the calculation is correct (Smith 2005).

The revised classic approach views that the states of nature of the corporate investments are divided into two types: market and private risks (Dixit, Pindyck et al. 1994). Real options analysis (ROA) is used when investments are dominated by the former type of risks, and dynamic programming or decision analysis (DA) should be applied when investment is dominated by the latter type. This method adds a second method to the classic approach to extend the problem to the case where private risks are dominating. The problem of the revised classic approach is that the two proposed methods are only able to value projects under two extreme states: either market risk dominated or private risk dominated.

Instead of dividing the investments into two extreme states, the Integrated Approach suggests that the states of nature of an investment can be decomposed into two components: public and private risks (Smith and Nau 1995; Smith and McCardle 1998). It is assumed that public risks can be hedge by a replicating portfolio and assigned with “risk neutral” probabilities; private risks are valued by expected net present value discounted at the risk-free rate and are assigned with subjective probabilities. An integrated decision tree is used to explicitly model public and private risks and rolled back to calculate the option value.

While the above three approaches utilize binomial lattice or tree to model the uncertainties and calculate , the Datar-Methews (DM) method apply Monte Carlo technique to model the uncertainties and determine the real option value of a project by using the average of positive outcomes of the project:

$$\text{Real option value} = \text{Average}\,[\text{Max}(\overline{\text{operating profits}} - \overline{\text{launch cost}}, 0].$$

where operating profits and launch costs are the appropriately discounted cash flows to time 0. Triangular distributions are used to simulate the cash flows.

Using variables similar to traditional option pricing, the DM formula is

$$C_0 = E_0[\max(S_T e^{-\mu t} - X_T e^{-rT})] \qquad (2.7)$$

where $\mu$ and $r$ are the discount rates, $S$ is the operating profit, and $X$ is the exercise or launch cost.

# 2.8 Research Gap Analysis

As described in Chapter 1, this research aims to provide two distinct but complementary approaches for embedding flexibility in engineering system design: a screening approach for technical options in system boundary, and a practical valuation approach for estimating the value of flexibility. Then the key questions are how the proposed approaches differ from previous research and what gaps in knowledge they address.

## 2.8.1 Motivation for a New Screening Approach

In Section 2.6, four screening approaches closely related to this research in real options identification were discussed in detail. Table 2-2 provides side-by-side comparison of the proposed screening approach with published screening approaches. Based on the review of the real option identification literature, the following gaps are identified.

1. Due to the complex engineering architecture and its interactions with multiple uncertainties in its operational environment, it is a great challenge to predict change propagation impact on system elements due to multiple external changes and to identify appropriate system elements to made technical change for flexibility. Kalligeros (Kalligeros 2006) and Suh are first attempts to identify promising system elements to design technical options. Despite many positives, there are two limitations of their screening approaches: they both focus on the physical domain and only direct change relationships are considered. (Bartolomei 2007) address the first limitation by extending the system representation from physical domain to social and environmental domains using ESM. However, he only provides a conceptualization. (Wilds 2008) extends Bartolomei's ESM methodology to explicitly consider multiple types of change relationship among system elements. The author also considers the combined risks via direct and indirect interactions. However, the change propagation analysis in Wild's methodology assumes the change impacts on one elements causing by other elements are mutually exclusive, thus the change prediction results are overestimated. Despite a couple of research efforts on identifying technical options in complex systems, it not apparent that any have posed a general screening approach which explicitly analyze how multiple external changes from social and environmental domain propagate to physical domain and the identification of potential system elements to incorporate flexibility based on the multiple external change impacts on system elements and their impacts to the whole system due to external changes.

2. The second research gap relate to the computational complexity associated with using CPM for analyzing change behavior of system elements. CPM depicts how initial change propagates from both direct and indirect components, and how combined risk of this change is calculated (Clarkson, Simons et al. 2001). However, the algorithm using numerical equations for combined probability and risks calculation requires a brute-searching of all possible change propagation paths from the initial element to a particular affected element. Other algorithms for approximation of the results either ignore the effect of cyclic paths or based on the assumption of independence between the direct edges also independence between the change propagation paths which leads to higher estimation of combined risks. In addition, the CPM only considers a single change cause and effect in the physical domain: only one initial change is considered. Complexity will increase when many external changes are considered simultaneously.

**Table 2-2 Comparison between this research and closely related researches**

| | Multi-Domain Analysis | Direct Flexible Candidate Identification | Combined Risk | Scale of Change | Multiple Environmental Uncertainties | Cyclic Effects |
|---|---|---|---|---|---|---|
| (Suh 2005) | | √ | | | | |
| (Kalligeros 2006) | √ | | | | | |
| (Bartolomei 2007) | √ | | √ | | | |
| (Wilds 2008) | √ | √ | √ | √ | | |
| This Research | √ | √ | √ | √ | √ | √ |

*(Bartolomei 2007) provides a conceptualization only.

## 2.8.2 Motivation for a New Valuation Approach

Despite the wide acceptance in academic research and a few implementations in practice, two fundamental conceptual difficulties of the practical real options approaches have hinder the adoption of ROV approaches for valuing various industrial projects and complex engineering systems.

The first difficulty is related to the MAD assumptions adopted by many practical ROV approaches (e.g. BDH and DM method). The MAD assumption uses an exogenously determined risk-adjusted discounted rate to calculate the present value of the underlying investment. It totally ignores the market information on the value of the investment or important elements of that investment.  The other difficulty is related to the GBM assumption. Although it may be reasonable to believe that the motion of equilibrium prices in highly liquid, widely accessible markets is followed by GBM, it is problematic to assume the subjective assessments of the value of the underlying investment should follow GBM. In fact, the assessed value of the underlying investments may be driven by specific events in specific time periods in a manner that looks nothing like “random drift” (Borison 2005). Nevertheless, current practical ROV approaches which use binomial lattice or tree to model uncertainties typically consider no more than two sources of risk at a time (Benaroch 2002). Different uncertainties are either separated into two parts and treated differently or combined into a single representative uncertainty by Monte Carlo simulation. In reality, most engineering systems are exposed more than two sources of risks, which cannot be easily separated into systematic (market-related) and market-unrelated (project-specific) components.

# 3 Real Options Identification in Complex Engineering Systems

## 3.1 Introduction

The successful value delivery of an engineering system through its entire lifecycle is greatly affected by uncertainties in its operational environment. These uncertainties may be due to changing customer requirements, dynamic market conditions (e.g. demand, price and cost) and evolving technology. Real options embedded into the system architecture allow ease of late changes in the system components or subsystems to accommodate changing environments. However, to capture the value of flexibility, additional expenditure must be first invested into the system to make technical modification or replacement which enables future changes in the system. For example, having the capability to switch production from one kind of automobile to another requires an extra capital investment in the early construction stage of flexible manufacturing systems. One of the most challenging tasks to incorporate flexibility in engineering systems is the identification of potential areas, which can be changed with relative less effort but contribute significantly to system performance under uncertainty. Screening models are proposed for the purpose of identifying the potential areas. The general requirements for an effective analytic screening model for real options "in" complex systems are:

1. It should be able to capture the characters of the main uncertainties (external changes) which will affect system performance in the management and operation environment of the system.

2. It should be able to model and analyze the change behaviors of subsystems or system components under uncertainties, in order to estimate the effect of subsystems or components to propagate change throughout the systems.

3. It should be able to provide metrics to determine which elements are required efforts to embed flexibility based on their change behaviors.

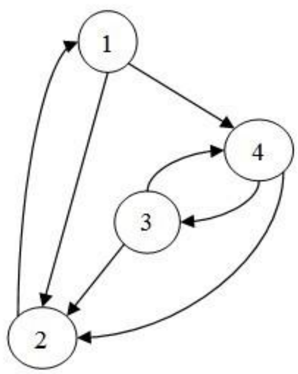
In the remaining of this chapter, a matrix-based simulation algorithm is developed in Section 3.2 to analyze the change behaviors of system elements. This simulation algorithm is able to predict change propagation effects from environmental uncertainties to system elements. Subsequently, a screening process is proposed Section 3.3 to identify the most promising locations in the system to create real options in the face of multiple system uncertainties.

# 3.2 A Matrix-based Simulation Approach for Change Prediction

## 3.2.1 Change Propagation Network and Change Propagation Tree

The complex change interactions among system elements can be modelled as a network, where changes propagate among the network elements only along the links connecting the network elements. The change propagation network can be represented by a directed graph (DG) which comprises a set of nodes and a set of directed edges connecting these nodes (illustrated in Figure 3-1). A node represents a system element and an arc indicates a change relationship between two connected elements. Assume that a directed graph is denoted as $G = \langle V, E \rangle$, where $V = \{v_1, v_2, ..., v_n\}$ is a set of nodes denoting $n$ elements, and

$E = \{e_1, e_2, ..., e_n\}$ is a set of directed edges denoting the path and the direction of change propagation. Each arc can be associated with a value between 0 and 1 to quantify the likelihood or impact of a direct change interaction. For instance, in Figure 3-1 an arc from node $1$ to node $2$ with a probability value $p_{1,2}$ implies a cause or effect dependency relationship: a change in node **2** will be caused by a change in node **1** with a probability of $p_{1,2}$, or a change in node $1$ will result in a change effect in **2** with a probability of $p_{1,2}$. The instigating node **1** can be viewed as a parent of the affected node **2**.




| | 1 | 2 | 3 | 4 |
|---|---|---|---|---|
| 1 | | 0.4 | 0 | 0 |
| 2 | 0.7 | | 0.4 | 0.2 |
| 3 | 0.3 | 0 | | 0.5 |
| 4 | 0.8 | 0 | 0.6 | |

**Figure 3-1 Example of directed graph (DG) and the corresponding DSM representation**

A cyclic path may exist in the DG. It indicates that an initial change in an element propagates back to that element through a number of intermediate elements. However, from system design perspective, cyclic effects are not allowed, since a cyclic effect will lead to 100% of change propagation likelihood and impact values, which will cause a disastrous consequence in system design. Redesign efforts should be taken to eliminate the cyclic effects by increasing tolerance margins on those cycle-causing elements. In CPM, cyclic change paths and self-dependences are not considered by assuming that system designers include the effects of such loops in the estimation of change impacts instinctually (Hamraz, Caldwell et al. 2012). Therefore, to predict the combined risk of change propagating from **1** to **2**, two cyclic paths are excluded by removing arc $\mathbf{2} \rightarrow \mathbf{1}$ and

$\mathbf{3} \rightarrow \mathbf{4}$. Figure 3-2 displays a directed acyclic graph (DAG) created from the example DG in Figure 3-1.

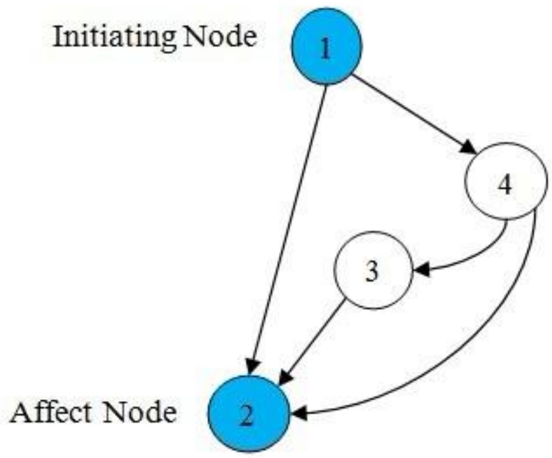



**Figure 3-2 An example of a directed acyclic graph**

All change propagation paths from node **1** to node **2** can also be visualized by a propagation tree (Figure 3-3). It is a tree representation of the DCG. In the propagation tree, paths returning to previously visited elements are not allowed.

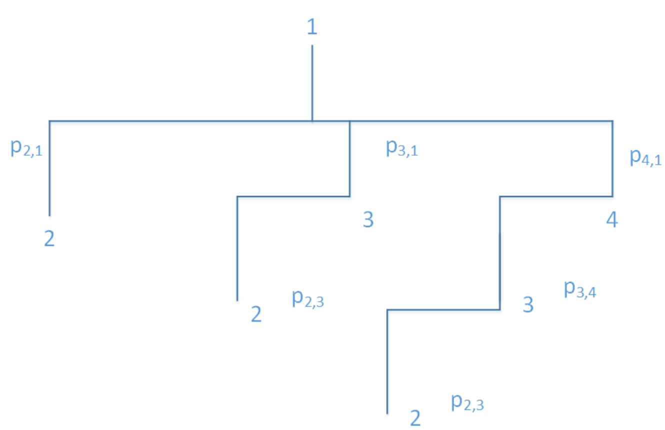



**Figure 3-3 A change propagation tree**

### 3.2.2 Proposed Matrix-based Simulation Approach

Propagation trees allow consideration of combined effect of a change in the node 2 caused by a change in the node 1 via both direct and indirect links. The original algorithm used in the CPM (Clarkson, Simons et al. 2001) views propagation tree as logic tree and calculates the combined effect by tracking each possible path between an instigating node to a specific affected node. The detailed evaluation process is presented in Section 2.6.5.2.

However, for large change propagation network, the original algorithm of CPM is computationally expensive due to a *brute-force* or *exhaustive* search in propagation tree and complex intersection and union operation in the joints of propagation paths. Several algorithms and tools have been applied to simplify the computation. The algorithm for *change favorable representation* (*C-FAR*) presented by (Cohen, Navathe et al. 2000) uses simple matrix multiplications without excluding cyclic paths. The *Trail counting algorithm* proposed by (Keller 2007) exhaustively searches all the paths in the propagation tree but uses only intersection operator to calculate end-to-end likelihood for each propagation path and then the union operator to combine these likelihoods of all propagation paths. This algorithm assumes that the change propagation paths are independent of each other. This leads to higher combined probabilities than the original algorithm of CPM. The *Matrix-Calculation-Based algorithm* described by (Hamraz, Caldwell et al. 2012) also adopts this assumption and applies matrix multiplications on modified likelihood DSM accounting for cyclic propagation paths. Bayesian network can also be applied for computing change propagation probabilities, if "Noisy-OR" assumption is made (Mirarab, Hassouna et al. 2007). Off-the-shelf software like Netica® can be used to build Bayesian network for change prediction. However, it requires *conditional probability table* (*CPT*) for each node. When the size of the network increases, the size of CPT also increases explosively. In the remaining of this section, a simple matrix-based simulation algorithm for computing combined likelihoods and risks is developed without using brute-force search and overestimating the combined probabilities.

#### 3.2.2.1 Proposed Algorithm for Directed Acyclic Graph (DAG) Construction

Before the simulation, a DAG is constructed to identify and exclude edges that will cause a cycle in the original DG. The construction process starts from an instigating node. Figure 3-4 displays the algorithm of DAG construction. The inputs are the original DG $G = \langle V, E \rangle$ , its associated likelihood DSM **L**, the instigating node **a**. The matrix element $l(v_i, v_j)$ of L indicates the existence of an edge from $v_i$ to $v_j$ .The purpose of the algorithm is to remove the cyclic paths from the DG and store the corresponding edges and nodes. The outputs are directed acyclic graph $G' = \langle V', E' \rangle$ , set of edges excluded $E_e$ and corresponding node set $V_e$ .The algorithm travels the DG in a breath-first fashion thus removes the cycle-causing edges as late as possible, and attempts to remove the edges that have the least impact on the DG.

Input: $G = \langle V, E \rangle$, **L** ,**a**
Output: $G' = \langle V', E' \rangle$, $E_e$ and $V_e$
$v_{selected} \leftarrow a$
$V_{next} \leftarrow V$
$V' \leftarrow \varnothing$
**while** $V_{next} \neq \varnothing$ && $Child(v_{selected}) \neq \varnothing$
    add node $v_{selected}$ to $V_a$ and delete node $v_{selected}$ from $V_{next}$
    **for** all $v_i \in V_{next}$
        **if** $l(v_{select}, v_i) \neq 0$ $(l \in L)$
            sort the value of $l(v_{select}, v_i)$ from large to small
            **for** each $l(v_{select}, v_i)$
                **if** adding $edge(v_{edge}, v_i)$ *does not cause a cycle*, **then**
                $E' \leftarrow edges(v_i)$, $V' \leftarrow v_i$, $V_{select} \leftarrow v_i$ ,$V_{next} \leftarrow V_{next} - v_i$
                **else**
                $E_e \leftarrow edge(v_i)$ ,$V_e \leftarrow v_i$, $l(v_{select}, v_i) \leftarrow 0$ .
        **else** $V_{next} \leftarrow V_{next} - v_i$

**Figure 3-4 Algorithm of DAG construction**

A reachable matrix **Re** is used to check cycles if a new edge is added into the DAG. In graph theory, reachability is the ability to get from one node **i** in a directed graph to another node **j**. In the reachable matrix **Re**, if **i** is able to reach **j** via direct or indirect edges, the corresponding entry $re_{ij}$ equals to 1. If there is a cycle between two nodes, they can reach themselves through the cycle, and thus the associated diagonal elements of **Re** equal to 1. The reachable matrix is also utilized in the proposed matrix-based simulation algorithm in the next section.

### 3.2.2.2 Calculation of Combined Likelihood

The proposed matrix-based simulation algorithm utilizes a simple Monte Carlo simulation to compute the combined probabilities and risks of change propagation from the instigating node to other nodes. First of all, in each run random variables are generated using Bernoulli distribution of probability in the DSM corresponding to the constructed DAG. A corresponding binary matrix **Q** is created. Next, a reachable matrix **Re** is generated for **Q**. If the reachable matrix element $re_{ka}$ ($k = 1,...,M$ , M is the number of nodes) in the column corresponding to the instigating node **a**, equals to 1, a counter $Count_{k,a}$ corresponding to the node **k** is incremented by 1. After N runs, the combined likelihood of **k** is then calculated as follows:

$$l_{k,a} = \frac{Count_{k,a}}{N} \tag{3.1}$$

### 3.2.2.3 Calculation of Combined Risk

The combined risk can be calculated in different ways according to different assumptions. The equation used to calculation combined risk proposed by (Clarkson, Simons et al. 2001) is given below. $r_{k,a}$ is the combined risk of change propagating to node **k** from **a**, where:

$$r_{k,a} = 1 - \Pi(1-\rho_{k,u}) \quad \text{and} \quad \rho_{k,u} = \sigma_{u,a}.l_{k,u}.i_{k,u} \tag{3.2}$$

where $\rho_{b,u}$ is the risk of change propagating from the penultimate node **u** in the path from **a** to **k**, $\sigma_{u,a}$ is the combined likelihood of change reaching **u** from **a** without going through **k**, $l_{k,u}$ is the direct likelihood of change propagating from **u** to **k** and $i_{k,u}$ is the direct impact of such a propagation. The values of $l$ and $i$ come from the direct likelihood and impact matrices. Values of $\sigma_{u,a}$ are calculated using the proposed algorithm in 3.2.2.2. In Equation (3.2) the combined risk $r_{k,a}$ weights the direct impact values of element **k** caused directly or indirectly by **a** with the combined probabilities of the change propagating from **a** to **k.**

However, in Equation (3.2), the impact of change in **k** directly caused by its single or multiple parent(s) together is calculated by multiplying the individual direct impacts of all of its parents (i.e., $\prod i_{k,u}$). Since $i_{k,u}$ is a normalized value (i.e., $i_{k,u} \in (0,1]$), $\prod i_{k,u} \leq i_{k,u}$. This means the multiple impacts are not greater than each individual impact. In this research, the multiple impacts are assumed to be the summation of all individual impacts $\sum i_{k,u}$. To compute the combined risk, the integer counter $Count_{k,a}$ in equation (3.1) is replaced with an impact counter $Impact_{k,a}$. In each run, $Impact_{k,a}$ is increased by $\sum i_{k,u}$. If the combined impact of a change in one node directly caused by multiple nodes can be estimated, the increment of the impact counter in each run is replaced. However, this requires more information.

### 3.2.2.4 Application of the Proposed Simulation Algorithm

The proposed simulation algorithm is applied to calculate the combined probabilities and risks of a five-element DAG. The direct likelihood and impact matrices are shown in Figure 3-5.

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | | 0 | 0 | 0 | 0 |
| 2 | 0.7 | | 0.2 | 0.2 | 0 |
| 3 | 0.3 | 0 | | 0.5 | 0 |
| 4 | 0.8 | 0 | 0 | | 0 |
| 5 | 0 | 0.5 | 0.7 | 0 | |

a. Direct Likelihood

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | | 0 | 0 | 0 | 0 |
| 2 | 0.8 | | 0.7 | 0.5 | 0 |
| 3 | 0.9 | 0 | | 0.4 | 0 |
| 4 | 0.4 | 0 | 0 | | 0 |
| 5 | 0 | 0.3 | 0.6 | 0 | |

b. Direct Impact

**Figure 3-5 Direct likelihood and impact matrices for a five-element change propagation network**

After 100,000 trials, the simulation results are shown in Figure 3-6. The calculated combined probabilities and risks of change propagating from **1** to **k** (*k = 2,3,4,5*) shown in the first column of the two matrices are the same as the ones calculated by equations in CPM proposed by (Clarkson, Simons et al. 2001)[2]. Results show that although node **5** is not directly affect by node **1**, the combined probability of change propagating from **1** to **5** is 0.63.

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | | 0 | 0 | 0 | 0 |
| 2 | 0.78 | | 0.2 | 0.28 | 0 |
| 3 | 0.58 | 0 | | 0.5 | 0 |
| 4 | 0.80 | 0 | 0 | | 0 |
| 5 | 0.63 | 0.39 | 0.42 | 0.34 | |

a. Combined Likelihood

| | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| 1 | | 0 | 0 | 0 | 0 |
| 2 | 0.52 | | 0.07 | 0.11 | 0 |
| 3 | 0.30 | 0 | | 0.15 | 0 |
| 4 | 0.32 | 0 | 0 | | 0 |
| 5 | 0.24 | 0.39 | 0.38 | 0.16 | |

b. Combined Impact

**Figure 3-6 Combined likelihood and risk matrices**

The Trail Counting algorithm and Matrix-Calculation based algorithm only compute the combined likelihood between a specific affected element **k** and the instigating element **a**. However, the proposed Monte Carlo simulation algorithm

[2] The results obtained from numerical equations of CPM are shown in Appendix

can provide the probabilities of a change in **k** caused by the change in the intermediate nodes which in turn are caused by a change in **a**. For instance, in one random trial, if a change in the instigating node **a** propagates to **k** through an intermediate node **u**, a counter $Count_{k,u}$ is increased by 1. These values are useful in predicting change propagation in multiple domains. The change propagation prediction in multiple domains analyzes the combined effects of change propagating from environmental uncertainties to system components or subsystems. Multiple external change scenarios will occur with an estimated probabilities and impacts. These changes will further propagate among system elements. The proposed simulation algorithm provide a tool to predict the combined effect of a particular system element affected by environmental uncertainties and also the combined effect of change in other elements caused by this particular elements under multiple change scenarios. In addition, the proposed algorithm for DAG construction is able to identify edges which will cause cyclic effects in the change propagation. The effect of identified edges and their associated nodes will be further considered in the following section.

## 3.3 Proposed Screening Process

This section presents a novel screening process to identify promising areas in the physical domain to plan and build in flexibility in the early conceptual design phase. It utilizes the matrix-based simulation approach proposed in Section 3.2 to estimate the combined probabilities and risks of change propagation among subsystems. A system level DSM – ESM, is employed to model the main domains of the system structure and map the environmental uncertainties to subsystems. It is then used to predict the change propagation behaviors of the system. By calculating two impact indicators (i.e. environmental impact-receiving and internal impact-supplying) of each subsystem, the candidate subsystems for flexibility and robustness are exploited. The flexible candidates can be changed to adapt to future uncertainties with less efforts, while the robust candidates should be insensitive to future uncertainties and serve as flexibility enablers to enable future modification or replacement in flexible candidates with acceptable expenditure. To explore the responsive behaviors of system components in response to environmental changes in a complex engineering system where cycle paths of changes may exist, the matrix-based simulation approach proposed in Section 3.2 is applied to proactively deal with loop effects and predicts the combined likelihoods and risks of propagating changes.

A six-step screening process is proposed to explicitly identify key subsystems for flexibility and robustness:

Step 1: Define system and its purpose and primary objective(s)

Step 2: Identify the main sources of uncertainties, which are external uncertain factors on future system environment or state affecting the system to deliver benefit to stakeholders, and estimate the possible impacts (upside opportunities and downside risks) and probabilities of each change scenario with respect to each uncertainty.

Step 3: Determine an initial design and performance measure for value assessment.

Step 4: Develop system representation by an ESM and assess the dependency strength of change interactions among ESM elements.

Step 5: Predict risks and opportunities of change propagation using the proposed matrix-based simulation approach.

Step 6: Identify critical subsystems for flexibility and robustness by differentiating types of subsystems based on two indicators (i.e. environmental impact-received and internal impact-supply)

Step 6: Quantify excepted opportunity and risk of change for each system component using the likelihoods and impacts information from step 3, 4 and 6.

## 3.3.1 Step 1: Define System, Identify Its Purpose and Objective(s)

Any design process begins by framing the design problems – constructing a simplified model of reality to reduce the complexities of the problem. A general start point of model construction is to elicit the design purpose and objective(s) in target. An Engineering system is designed for a purpose. System designers should know the immediate purposes of the system by asking "What does the system accomplish?" They should also know the opportunities, current issues and challenges of the system. Answers can be drawn from academic research, practical experiences, historical and potential development of the system, and related systems with similar functionalities or structures. The preliminary design objective(s) should be clarified to capture the concerns of the stakeholders (e.g. system holders, system designers, managers, operators and customers, etc.). Each objective can be decomposed into functional requirements.

## 3.3.2 Step 2: Identify Main Sources of Uncertainties and Predict Possible Change Scenarios

Obviously, flexibility is valuable only when there are environmental Uncertainties (system drivers). In the early conceptual stage, main sources of uncertainty in the operational environment are (1) dynamic marketplace (regarding customers' requirements, demands, operating cost, etc.); (2) evolving technologies whose life time often shorter than system life cycle; (3) changing integration environment where a system has complex interactions with other necessary system. Uncertainties are usually characterized by various change scenarios and associated probabilities. In this step main uncertainties are defined by:

1. Brainstorming the critical change scenarios which describe the possible future states.

2. Estimating the impact (opportunity) and probability of each change scenario.

Future states of a system uncertainty can be different mission requirements, demands, applications and available operational modes in the future. For example,

The environmental impact of each change scenario on the system is defined as the product of its opportunity and the corresponding likelihood. The term "opportunity" refers to the effects of uncertainties (both positive and negative) which drive the need for embedding flexibility in the system design. The likelihood is the possibility of the change occurring. This terminology is borrowed from risk management which is used for the identification, assessment and prioritization of risks. Hence, similar to risk graph in risk management, a square matrix is utilized to represent the opportunity and likelihood of critical change scenarios as in Figure 3-7. The change scenarios in the top right-hand corner of the matrix are very likely to occur and have high impact on the system's ability to deliver value to its stakeholders. The change scenarios in low left-hand corner are lowly probable and have lowest impact.

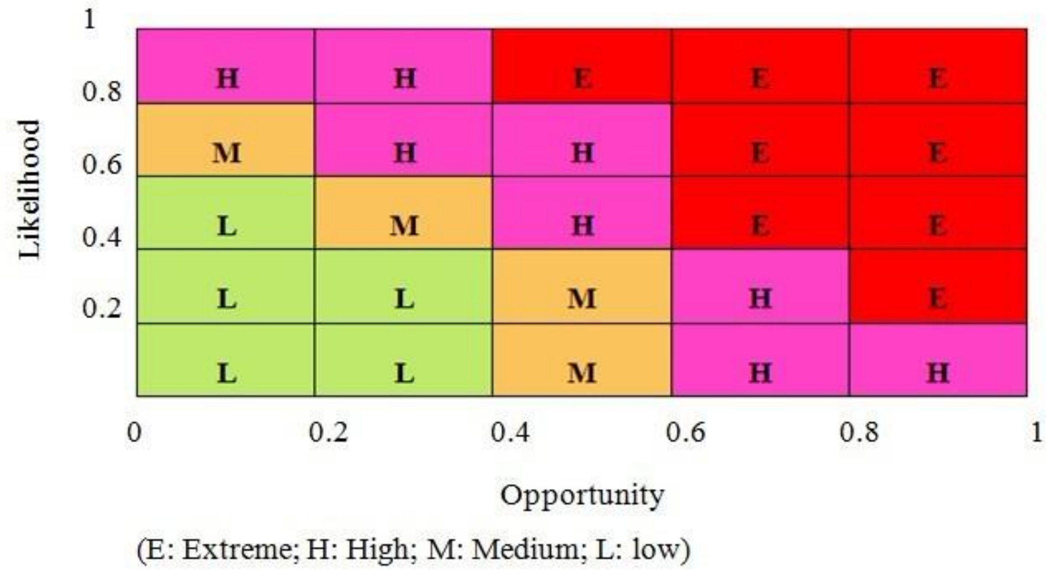



**Figure 3-7 The assessment matrix for change scenarios**

### 3.3.2.1 Likelihood of Change Scenarios

Classical methods are utilized for scoring change scenarios based on a consolidation of previous experience and expert judgment. In the assessment matrix, qualitative scales are used to score probabilities of change scenarios with 5 levels:

1. Definite: 80% to 100% chances of occurrence. The change scenario is almost certain to show-up during the system management and operation stage. The score assigned to this level is 1.

2. Likely: 60% to 80% chances of occurrence. This level is scored by 0.8.

3. Occasional: 40% to 60% chances of occurrence. This level is scored by 0.6.

4. Seldom: 20% to 40% chances of occurrence. The change scenario has a low probability of occurrence but still cannot be ruled out completely. This level is scored by 0.4.

5. Unlikely: less than 20% chances of occurrence. This level is scored by 0.2.

#### 3.3.2.2 Opportunities of a Change Scenario

The opportunities (or impacts) of a change scenario can also be ranked and classified into 5 levels based on how much impact it will have on the system's ability to provide long lasting value to its stakeholders over its lifecycle:

1. Insignificant: A scenario will have a near negligible amount of impact on the life cycle value (LCV) of the system. This level is scored by 0.2.

2. Marginal: A scenario will have relative small impact on the LCV of the system. This level is scored by 0.4.

3. Moderate: A scenario will not have a great but yet sizable impact on the system's LCV. This level is scored by 0.6.

4. Promising: A scenario will cause a high change on the system's LCV. This level is scored by 0.8.

5. Critical: A scenario will have a very high impact on the system's LCV. This level is scored by 1.

However, the system's LCV is difficult to quantify, let along in the conceptual stage. Hence, the opportunity of a scenario is more appropriately adjudicated by qualitative assessments on the critical factors of LCV, like key performance requirements, profits/ utility and strategic importance (Pierce 2010).

#### 3.3.2.3 Assessment Matrix of Change Scenarios

Once the appropriate likelihood and opportunities of change scenarios are distilled, the qualitative expected values of each change scenario are classified into four categories (i.e. extreme, high, medium, and low) which indicate the potential need for flexibility in the system design. Each category is visualized by different colours in the matrix (illustrated in Figure 3-7.

### 3.3.3 Step 3: Determine an Initial Design and Value Assessment

The baseline design, also referred to as “inflexible design”, is assumed to exist and satisfy originally intended purposes of the system without considering future uncertainties. They can be determined by building upon previous knowledge of similar systems or by optimizing system performance under deterministic environmental conditions and constraints. The existence of the baseline design allows evaluating real options as an additional ability of the systems to be able to adapt to possible change scenarios.

### 3.3.4 Step 4: Develop System Representation and Assess Change Dependency

In this section, a system-level DSM, engineering system matrix (ESM) is constructed to represent the system elements and describe the links among these elements based on the previous knowledge of similar systems. An ESM is an enhancement DSM representation of engineering system. It extends the system boundary to contain both internal elements in technical aspect and external elements in social and environmental aspects. The ESM methodology provides a framework to map environmental Uncertainties to functional requirements, depict the changes spreads from environmental domain to physical domain, and quantify the probabilities and impacts (e.g. cost, time) of the direct design change influence.

#### 3.3.4.1 Basic DSMs in an ESM

(Bartolomei 2007) provide a comprehensive ESM representation of an engineering system. The ESM includes a number of DSMs in different domains. Based on design purposes, requirements and available information during each stage of the design process, an ESM can be constructed with different levels of abstraction. For instance, to reduce the complexity of the analysis, the screening process can be first applied on higher levels of abstraction in system architecture, like subsystem-level, and identifies subsystems as candidates for flexibility design opportunities. Then those selected subsystems can be further decomposed into component-level. Similar screening process can be applied on the component level and identifies components as flexibility opportunities.

This research mainly focuses on three domains: environmental domain represented by system drivers DSM, functional domain represented by functional requirements DSM and physical domain represented by subsystem DSM. Uncertainties in environmental domain can propagate to physical components through changes in functional requirements (illustrated in Figure 3-8). Interrelationships between different domains can be captured by corresponding DMMs. These DSMs and DMMs are then organized in a single matrix representation – ESM. The existence of links between system elements in multiple domains can be denoted by “1” or “X” in the entries of the ESM.

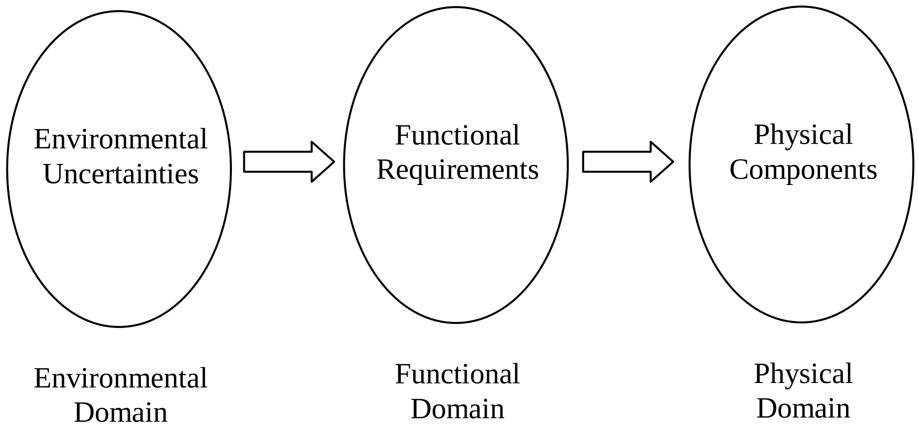



**Figure 3-8 Three main system domains**

The system drivers (SDs) are the economic, technical, social and political uncertain variables that affect lifecycle value of a system and beyond the stakeholders' control. For instance, the value of an UAV manufacture plant may be affected by demand, changing customer requirements, new technologies and government regulations. The main SDs are identified in step 2. If change scenarios with respect to future states are properly specified so that each change scenario only describes a possible future state of one SD, all SDs can be independent with each other.

The purpose, objective(s) and FRs in the functional domain are specified in step 1. Engineering systems are systems of purpose and usually have clear objective(s). An objective or mission is defined by a set of FRs. A function is what a system must do or accomplish to achieve one of its system objectives (Suh 2001). The value of a system to its stakeholders is realized by accomplishing these functional requirements. For example, an Unmanned Aerial Vehicles (UAV) is designed to satisfy the customer needs for finding and following specified targets. This mission requirement, search and reconnaissance, can be decomposed into FRs of the range and time on target.

The physical elements (e.g. components subsystems) and the interactions among these elements are identified to represent system architecture. Relationships between components can be classified into spatial, energy, information and material type based on (Pimmler and Eppinger 1994).

To identify the promising regions for flexibility, one must know how the environmental Uncertainties drive the internal changes within the system. In this research, three types of dependency matrices should be identified: environmental –functional domain mapping matrix and functional-physical components domain mapping matrix, and physical element-element interacting matrix (e.g. subsystems DSM and components DSM). The first matrix depicts change interactions from the external (environmental) uncertainties to internal elements within the system boundary. The latter two matrices depict change interactions inside the system boundary. By domain-mapping, the change relationships between environmental uncertainties and physical elements are obtained.

### 3.3.4.2 Environmental – Functional Domain Mapping Matrix

The environmental-functional domain mapping matrix translates the mission needs for each scenario into a verbal, non-form specific description of system functions (Pierce 2010). Each FR should be properly defined so that it is independent of each other, that is, a change in one FR will not instigate a change in another FR. The interdependency among FRs, which can be achieved by providing very specific change scenarios in step 2, simplifies further analysis of change behaviour.

### 3.3.4.3 Functional – Physical Domain Mapping Matrix and Component-Component Matrix

In the system boundary, the functional-physical domain mapping matrix captures the change relationships from FRs into physical elements. The physical elements DSM captures the interdependencies among components and/or subsystems. To identify the change dependencies insider the system boundary, two-step change dependency identification is conducted:

1. Identify direct change relationships from FRs to subsystems by asking the question: "If a change in a FR occurs, which subsystems will be affected?" The subsystem directly affected by the FR is called as a *change initiator*.

2. Identify direct change relationships among subsystems by asking the question: "If a subsystem is changed due to other external or internal change, what other subsystem will be affected by this change?"

Therefore, the change relationships between SDs and subsystems can be obtain by mapping change relationships from SDs to FRs, and then from FRs to subsystems. Figure 3-9 displays an extended DSM which is a combination of SDs DSM, subsystems DSM and the corresponding DMMs. This extended DSM can be viewed as an ESM with only two domains. It is the matrix representation of a change propagation network. If there is a precedence relationship between a row and column elements, a "1" is inserted in the corresponding matrix entry. Figure 3-10 is the corresponding directed graph (DG) representation.

| | $SD_1$ | $SD_2$ | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ |
|---|---|---|---|---|---|---|---|---|---|
| $SD_1$ | | | | | | | | | |
| $SD_2$ | | | | | | | | | |
| $S_1$ | 1 | 1 | | | | | | | |
| $S_2$ | | | 1 | | 1 | | 1 | 1 | |
| $S_3$ | 1 | | 1 | | | | | | |
| $S_4$ | | | | 1 | 1 | | | | |
| $S_5$ | | | | | | 1 | | | |
| $S_6$ | | | | 1 | | | | | |
| $S_7$ | | | | | 1 | 1 | | | |

**Figure 3-9 An extended DSM composed of SDs DSM, subsystem DSM and the corresponding DMMs**

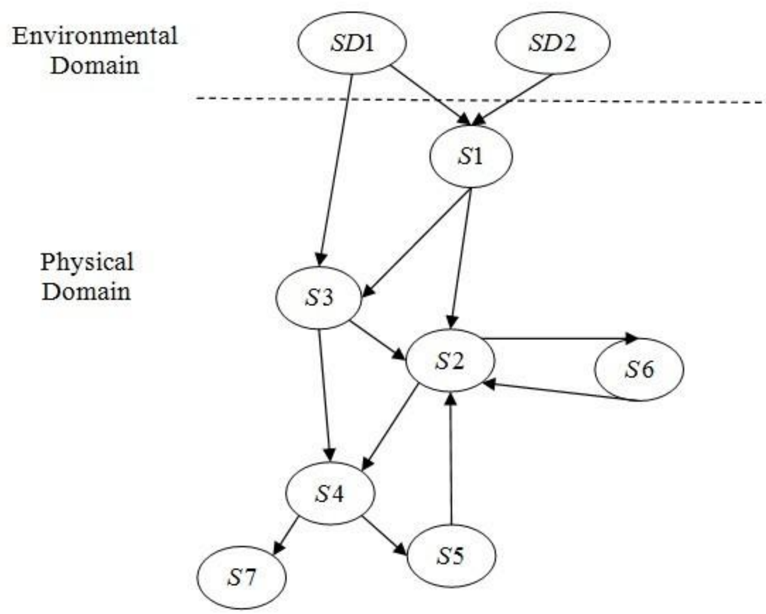



**Figure 3-10 A graph representations of change propagation network**

### 3.3.4.4 Assess Dependency Strength in ESM

Most systems are designed with *buffers* which can absorb some degree of change to provide certain tolerance margins (Eckert, Clarkson et al. 2004). When the tolerance margins are exceeded due to the increased strength of incoming change, the buffers will generate more change than they can absorb and propagates the change. Therefore, the predicted change propagation behaviors will be contingent on primitive assessment on the strengths of incoming changes. The step is to estimate the dependency strengths of the change relationships in the ESM constructed in step 4.

In CPA the expected scale of a change instigated by others is often assessed by the product of likelihood and impact. Change likelihood is defined as the average probability that a change in the design of a physical element will be triggered by a design change in another by directly propagating through their common interface (Clarkson, Simons et al. 2001). Likewise, impact is defined as the average proportion of the redesign work caused by change propagations. Interviews with designers are conducted to qualitatively assess the impact and probability of each design change triggered by another change.

**Impact of Change**

In this research, the impact of a change in one system element caused by others is defined as the cost associated with the technical modification or replacement of the element in response to an incoming change (Suh 2005). It is the cost of engineering redesign, addition fabrication and assembly tooling/equipment investment required for design change to enable the system to adapt to external change. The switch cost of each system element is then normalized to a number between 0% and 100% with 0% representing the lowest switch cost and 100% representing the highest switch cost.

**Probability of Change**

The probability of a change caused by an incoming change is conditional on the scale of the incoming change. The sensitivity DSM methodology proposed by Kalligeros (2006) utilizes interviews to elicit domain experts' knowledge about the sensitivity of each design parameter in response to change in each functional requirement. Similarly the probability of a change in a subsystem instigated by a change in a FR can specified by asking “If a certain amount of change $y_i$ occurs in a FR $i$ ($i=1,...,n$; $n$ is the number of the FRs), what is the probability that a certain amount of change $x_k$ will occur in a subsystem $k$ ($k=1,...,m$ ; $m$ is the number of subsystems)?” The probability of a change in a subsystem instigated by a change in other subsystem can be estimated in the similar way. If more information is available, for instance the FRs DSM and subsystems DSM can be further decomposed into low level of abstraction, the change probability can better estimated by investigating the relationships between these lower level elements.

## 3.3.5 Step 5: Predict Change Propagation Impacts Using the Proposed Matrix-Based Simulation Approach

### 3.3.5.1 Cyclic Change Effect

One limitation when directly applied CPM to explore the real options in system design is that cyclic paths are excluded before the computation predictive matrices, thus the impacts of elements which may cause cyclic effects are underestimated for change behaviors analysis. Current algorithms of change prediction method for computing combined predictive matrix are based on the assumption that cyclic change paths and self-dependences are not considered in the analysis (Hamraz, Caldwell et al. 2012). This assumption is required to avoid infinite changes propagating cycle effects. A loop or a cyclic path is a path which passes through at least one element twice or more. For example, in Figure 3-11, suppose a change in element **1** occurs. It then trigger changes in the subsequent elements and propagates back to **1** from element **2**. The element which propagates change back to the initial change element is defined as a cycle-causing element and the edge from the cycle-causing element to the initial change element is defined as a cycle-causing edge in this thesis. When the loops are small the designers are able to include the effects of such loops by estimating a higher impact value for cycle-causing elements. However, when there are many elements in a system, it is possible that a change from an initial element may propagate through a number of intermediate elements and return to that initial element. Since the estimations of change impacts are performed before the change prediction, it is very likely that the system designers are unable to foresee such loops, thus the impacts of some elements are underestimated. To overcome this limitation, the cycle-causing edges and the associated elements are first identified and the impacts of these elements are re-estimated for further change behaviors analysis.

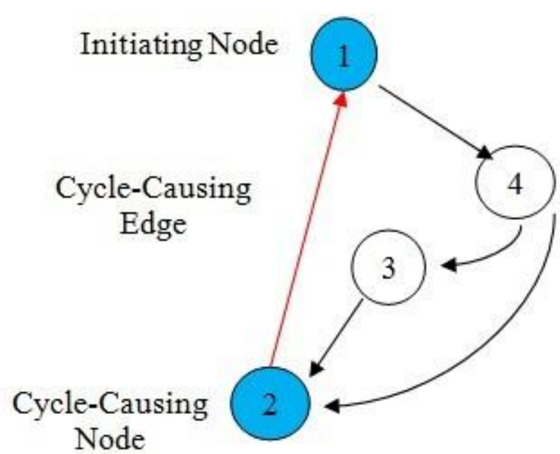



**Figure 3-11 An example cyclic path**

#### 3.3.5.2 Prediction of Change Propagation form Environmental Uncertainties to System Elements

The matrix-based simulation approach proposed in Section 3.2 is utilized to predict the effects of change propagation from environmental uncertainties to physical elements. First of all, the edges which cause cycle in the change propagation network and the associated elements are identified and stored. Then the proposed matrix-based simulation algorithm is performed to calculate the combined probability and risk of each subsystem caused by multiple environmental uncertainties. The environmental impact of each subsystem received can also be calculated by the proposed simulation algorithm. The environmental impact of a subsystem affected by environmental uncertainties is defined as the combined opportunities of all identified change scenarios that directly or indirectly influence the subsystem. The opportunities of identified change scenarios are estimated in Step 2, Section 3.3.2.

The change propagation network represented by the DG in Figure 3-10 is used as an example for the analysis. Edges $S_6 \rightarrow S_2$ and $S_5 \rightarrow S_2$ are identified as cycle-causing edges, and removed from the DG. Let **L** be the likelihood matrix of the corresponding DAG. In addition, the probabilities of change scenarios in $SD_1$ and $SD_2$ are 0.4 and 0.6 respectively. A new column representing an event generator (EG) is added into original matrix **L** where the elements in the second and third row represent the probabilities of the two change scenarios. Figure 3-12 and Figure 3-13 displays the extended likelihood and probability matrices **L'** and **I'**, respectively.

| | $EG$ | $SD_1$ | $SD_2$ | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $EG$ | | | | | | | | | | |
| $SD_1$ | 0.4 | | | | | | | | | |
| $SD_2$ | 0.6 | | | | | | | | | |
| $S_1$ | | 0.3 | 0.6 | | | | | | | |
| $S_2$ | | | | 0.6 | | 0.7 | | | | |
| $S_3$ | | 0.7 | | 0.3 | | | | | | |
| $S_4$ | | | | | 0.8 | 0.5 | | | | |
| $S_5$ | | | | | | | 0.2 | | | |
| $S_6$ | | | | | 0.5 | | | | | |
| $S_7$ | | | | | | 0.6 | 0.2 | | | |

**Figure 3-12 Direct likelihood matrix L'**

| | $EG$ | $SD_1$ | $SD_2$ | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $EG$ | | | | | | | | | | |
| $SD_1$ | 0.7 | | | | | | | | | |
| $SD_2$ | 0.5 | | | | | | | | | |
| $S_1$ | | 0.4 | 0.4 | | | | | | | |
| $S_2$ | | | | 0.6 | | 0.5 | | | | |
| $S_3$ | | 0.6 | | 0.5 | | | | | | |
| $S_4$ | | | | | 0.5 | 0.4 | | | | |
| $S_5$ | | | | | | | 0.2 | | | |
| $S_6$ | | | | | 0.5 | | | | | |
| $S_7$ | | | | | | 0.5 | 0.2 | | | |

**Figure 3-13 Direct impact matrix I'**

| | $ES$ | $SD_1$ | $SD_2$ | $S_1$ | $S_2$ | $S_3$ | $S_4$ | $S_5$ | $S_6$ | $S_7$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $ES$ | | | | | | | | | | |
| $SD_1$ | 0.28 | | | | | | | | | |
| $SD_2$ | 0.30 | | | | | | | | | |
| $S_1$ | 0.19 | 0.05 | 0.14 | | | | | | | |
| $S_2$ | 0.27 | 0.14 | 0.18 | 0.22 | | 0.13 | | | | |
| $S_3$ | 0.23 | 0.19 | 0.05 | 0.06 | | | | | | |
| $S_4$ | 0.22 | 0.17 | 0.12 | 0.15 | 0.05 | 0.18 | | | | |
| $S_5$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.02 | 0.04 | 0.02 | | | |
| $S_6$ | 0.12 | 0.06 | 0.07 | 0.08 | 0.09 | 0.10 | | | | |
| $S_7$ | 0.11 | 0.09 | 0.04 | 0.05 | 0.01 | 0.12 | 0.03 | | | |

**Figure 3-14 Combined risk matrix**

The calculated combined risks with 100,000 trials are shown as in Figure 3-14. Each entry number in the first column of the matrix in Figure 3-14 is the combined risk of a change occurring in the subsystem $S_i$ ( $S_i$ is the corresponding row head of the likelihood matrix) affected by all environmental uncertainties. Each entry number in the second and third column of the matrix in Figure 3-14 is the combined risk of a change in $S_i$ triggered by a change in SD1 and SD2 respectively. Each value in the following column is the combined risk of a change in $S_i$ caused by a change in other subsystem, which in turn is caused by all environmental uncertainties.

From the combined risk matrix, the *internal impact-supply* (*II-S*) of a subsystem can be computed. The II-S of a subsystem $S_k$ is a measure of how $S_k$ influences other if $S_k$ is required to be changed in response of environmental uncertainties. The calculation of $\mathrm{II-S}(S_k)$ is defined as follow:

$$II - S(S_k) = r(S_k) + \sum_{l=1}^{m} r(S_k, S_l) \tag{3.3}$$

where $r(S_k)$ is the combined risk of changes in $S_k$ caused by all identified environmental uncertainties. $r(S_k, S_l)$ is the combined risk of changes in $S_l$ caused by changes in $S_k$, which in turn caused by environmental uncertainties.

The *environmental impact-received* (*EI-R*) of a subsystem is a measure of how each subsystem is affected by all identified environmental uncertainties. It is defined as the combined opportunities of all identified change scenarios that directly or indirectly influence the subsystem. The EI-R of a subsystem $S_k$ affected by a change scenario $CS_i$ is defined as the product of the combined probability of the subsystem $S_k$ affected by the change scenario $CS_i$ and the opportunity of this change scenario $o_i$.

$$EI - R(\mathrm{S}_k; \mathrm{C}\,S_\mathrm{i}) = o_\mathrm{i} \times l(CS_i, S_k) \tag{3.4}$$

where $l(CS_i, S_k)$ is calculated combined likelihood of a change in $S_k$ triggered by a change scenario $CS_i$ and $o_i$ is estimated in step 2. Therefore $\mathrm{EI-R(S_k)}$ is the combined opportunity (CO) of all identified change scenarios that directly or indirectly influence the subsystem:

$$EI - R(\mathrm{S}_k) = CO(S_k; CS_1, ..., CS_n) \tag{3.5}$$

where $n$ is the number of change scenarios. The combined opportunity $CO(S_k;CS_1,...,CS_n)$ weights the opportunity of each change scenario $CS_i$ with the combined probability of the subsystem $S_k$ affected by the change scenario $CS_i$. The calculation combined opportunity of $S_k$ is similar to the calculation of combined impact: in each trial of the simulation, an opportunity counter $Opp_k$ is increased by $\sum o_{k,i}$ , if a change in $S_k$ occurs due to the environmental uncertainties. Table 3-1shows the values of $EI-R$ and $II-S$ for each subsystem.

**Table 3-1 The calculated EI-R and II-S**

| Subsystem | $EI-R$ | $II-S$ |
|---|---|---|
| 1 | 0.27 | 0.77 |
| 2 | 0.26 | 0.57 |
| 3 | 0.25 | 0.77 |
| 4 | 0.25 | 0.25 |
| 5 | 0.03 | 0.01 |
| 6 | 0.13 | 0.12 |
| 7 | 0.15 | 0.11 |

## 3.3.6 Step 6: Identify Critical Subsystems for Flexibility and Robustness

There are two ways to cope with uncertainties in a system with various interconnected subsystems: (1) make a subsystem insensitive by increasing its change margins to change scenarios (robustness); and (2) make a subsystem modular thus is able to be changed without influencing many other subsystems (flexibility).

This research identifies critical areas for flexibility and robustness based on the two proposed indicators. A high $EI-R$ indicates that a subsystem is highly influenced by environmental uncertainties, thus is more likely to be changed. A high $II-S$ indicates that a high degree of risk due to the change in the particular subsystem. Figure 3-15 portrays the two indicators $EI-R$ and $II-S$ of each subsystem as orthogonal dimensions. Subsystems can be classified into four classes[3].

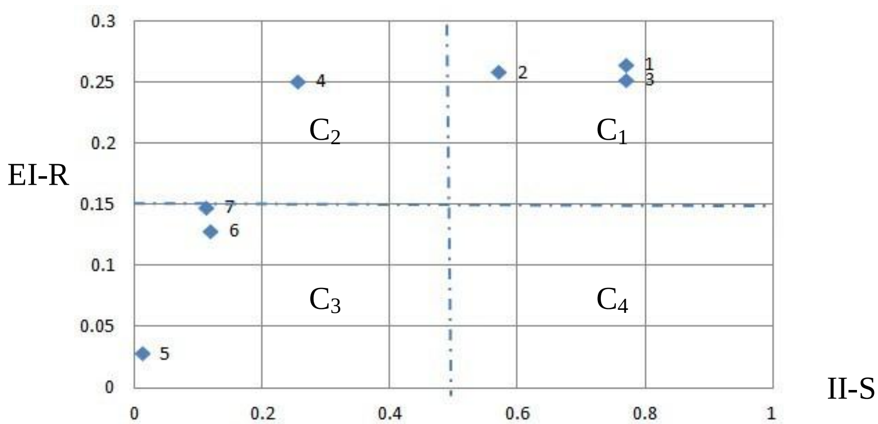



**Figure 3-15 EI-R and II-S of subsystems**

[3] The classification of subsystems is assumed to be dependent on system designers' utility function. How to classify subsystem according to their attributes and the determination of utility functions fall into the scope of statistic classification, machine learning, and pattern recognition Michie, D., D. J. Spiegelhalter, et al. (1994). "Machine learning, neural and statistical classification.", Bishop, C. M. and N. M. Nasrabadi (2006). Pattern recognition and machine learning, springer New York..

The following recommendations are presented to identify critical subsystems for flexibility:

1. The prime candidates for flexibility are subsystems with relatively high EI-R and II-S. They are likely changed in response to high degree of environmental uncertainties. They will also cause relative high impact on the system. A high *II-S* of a subsystem is caused by a high impact/switch cost of the subsystem itself caused by environmental uncertainties, and/or a high degree of propagation of change in the subsystem to others. Modularizing these subsystems by adding interfaces specific by *design rule* between the carriers with other subsystems provides a real option to be substitute/switch latter (Baldwin and Clark 2000). For instance, the payload of an Unmanned Aerial Vehicles (UAV) is changed frequently for different mission requirements. It is integrated with other subsystems, like fuselage, in a fixed UAV. Hence a change in the payload thus will propagate change to those subsystems. A flexible UAV is designed with a modular payload bay which is connected with the fuselage via the payload pod. This allows the payload bay contents for various sensor packages.
2. The subsystems with high EI-R and low II-S should also be examined for flexibility. They are likely to be changed in response to high degree of environmental uncertainties. Yet, they have relatively low impact on the system, thus can be easily changed in response to future changes.
3. The prime candidates for robustness are subsystems with low EI-R yet high II-S. If the *II-S* of a subsystem is high while its *EI-R* is relatively low or medium, the change in the subsystem has relatively high propagation strength. The later changes occur in these subsystems, the higher impact/costs are required for these changes. System designers should consider making these subsystems to be insensitive (robust) to change by increasing their change margins. For instance, the fuselage of a UAV can be viewed as multipliers. They are difficult to be changed once built. If other subsystems of the UAV are changed to accommodate new mission

requirements (e.g. the shape of the wings covered win an extensible material over a flexible composite structure can be changed to provide different lift requirements), the fuselage has to be change as well. However, rebuild the fuselage once the UAV is field will cause a very high cost. Therefore, the fuselage has to be overdesigned by creating housing for the flight components, data-collecting instruments and surveillance equipment, etc (Abdulrahim and Cocquyt 2000).

4. The subsystems which will cause cyclic effect can be flexible or insensitive depending on the number of their associated cycle-causing edges. The more cycle-causing edges from an affected subsystem to the initial subsystems, the higher interconnections between the affected subsystem with other subsystems. Considering that edges $S_6 \rightarrow S_2$ and $S_5 \rightarrow S_2$ are removed before the change prediction, the impact of subsystem **5** and **6** must be re-estimated and redesigned. To eliminate the cyclic effects, one way is to add interfaces specific by design rule between **5** and **2**, **6** and **2**. The subsystem **5** and **2** or **6** and **2** become independent with each other. Each independent subsystem creates a real option to be substitute in response to future change. However, if subsystem 5 or 6 also interconnects with other subsystems via cycle-causing edges, adding the proper interface become difficult. Another way is to increase the change margins of **5** and **6**, which is made these subsystems more insensitive to change. However, this will cause a high initial capital investment.

## 3.4 Summary

This chapter firstly develops a matrix-based simulation approach for change propagation prediction. Subsequently, a six-step screening process utilizing the developed matrix-based simulation approach multiple uncertainties is presented. This screening process provides recommendations for identifying critical subsystems for flexibility and robustness, based on change propagation analysis.

In particular, two indicators (i.e., EI-R and II-S), are proposed to facilitate the measurement of the combined effects of direct and indirect change propagation.

# 4 Real Options Valuation in Complex Engineering Systems

## 4.1 Introduction

Valuation is an important step in the early stage of system design. ROA is not only a valuation tool assessing the returns of the investments under uncertainty for stakeholders, but also a decision-support tool providing design and operation decisions for management to adapt to future change over the life-time of the system. The previous chapter developed a process to identify flexible opportunities embedded in complex system when facing multiple sources of uncertainty. This chapter presents how to guide the decision makers to design appropriate flexibility into the system through ROA results. Based on a recent developed technique for real options valuation (Datar, Mathews et al. 2007), an integrated approach which combines risk-adjusted cash flows simulation and decision tree technique is proposed in this chapter.

Real options in complex systems are relatively difficult to evaluate compared to financial options. The main reason is that complex systems are often designed and operated under multiple uncertainties (e.g., technical uncertainties and market uncertainties). Another main reason is that the time to exercise of various real options in complex systems is different and uncertain. Therefore, to valuate real options in complex systems requires the valuation method has the capability to model the effects of multiple uncertainty and encode various decision rules in different timing.

## 4.2 Risk-adjusted Cash flows Simulation

The risk characters of the investment are assumed to be divided into two parts: market-relate risk which can be replicated or hedged in the capital markets and project-specific risk which cannot. In addition, stakeholders owning the firm or the engineering system are assumed to be well-diversified and thus to be risk-neutral towards project-specific risk.

In financial literature, the growth rate of cash flows $x_i$ for an investment at a small time interval $\Delta t$ can be assumed to follow a normal distribution:

$$x_i(\Delta t) \sim N(\mu_i \Delta \mathrm{t}, \sigma_i^2 \Delta \mathrm{t}) \tag{4.1}$$

The stochastic differential equation (SDE) equivalent is

$$\begin{aligned} dx_i &= \mu_i dt + \sigma_i dz \\ dz &= \varepsilon \sqrt{dt} \end{aligned} \tag{4.2}$$

where $dz$ is a general Wiener process, and $\varepsilon$ is a normal (0, 1) distribution.

Then the return of the cash flows $S_i$ is followed by the GBM:

$$\frac{dS_i}{S_i} = x_i = \mu_i dt + \sigma_i dz \tag{4.3}$$

The discrete form of this process is

$$S_i(t+\Delta t) = S_i(t)\exp[(\mu_i - \frac{\sigma_i^2}{2})\Delta t + \sigma_i \varepsilon \sqrt{\Delta t}] \tag{4.4}$$

The rate of return of a market index (e.g. stock, stock index, market portfolio) in any small time interval $\Delta t$ can also be assumed to have a normal distribution:

$$m(\Delta \mathrm{t}) \sim N(\mu_m \Delta \mathrm{t}, \sigma_m^2 \Delta \mathrm{t}) \tag{4.5}$$

and a correlation coefficient $\rho_{mx}$ with the growth rate of cash flows $x_i$ .

According to equilibrium model of asset prices (Cox, Ingersoll Jr et al. 1985; Dixit, Pindyck et al. 1994), the risk-neutral drift or growth rates of cash flow $i$ is given by

$$\mu_i^* = \mu_i - \lambda_i \tag{4.6}$$

where $\lambda_i$ is the market risk premium of the underlying asset which depends on the correlation of the risk factors of the investment with other risks in economy.

In the capital asset pricing model (CAPM) (Sharpe 1964; Lintner 1965) the market risk premium of a specific investment $i$ is:

$$\lambda_i = \beta_i (r_m - r_f) \tag{4.7}$$

where $r_f$ is the risk-free rate, $r_m$ is the expected return on the market portfolio, $\beta_i$ is the market beta of the specific investment which measures the covariance of the investment with the market portfolio. It is given by

$$\beta_i = \rho_{im} \frac{\sigma_i}{\sigma_m} \tag{4.8}$$

where $\rho_{im}$ is the correlation of the specific investment and the market, $\sigma_i$ and $\sigma_m$ are the standard deviation of the investment and market.

In CAPM the market price of risk uncorrelated to the market is assumed to be zero. Hence, utilizing this equilibrium approach, the net present value of cash flows for the investment is expressed by the following equation:

$$S_0(\mathrm{T}) = S(0)\,\mathrm{e}^{(\mu^* - \frac{\sigma_i^2}{2})T + \sigma_i \varepsilon \sqrt{T}}\, e^{-r_f T}$$
$$= S(0) e^{(\mu - \frac{\sigma_i^2}{2})T + \sigma_i \varepsilon \sqrt{T}}\, e^{-[r_f + \rho_{im} \frac{\sigma_i}{\sigma_m}(r_m - r_f)]T} \qquad (4.9)$$
$$= S(T) e^{-[r_f + \rho_{im} \frac{\sigma_i}{\sigma_m}(r_m - r_f)]T}$$

Therefore, the present value of a European call option payoff for the $k^{th}$ simulated path can be expressed as:

$$O_0(T)_\mathrm{k} = \max\{S(T)_\mathrm{k}\, e^{-[r_f + \rho_{im} \frac{\sigma_i}{\sigma_m}(r_m - r_f)]T} - Xe^{-r_f T}\} \qquad (4.10)$$

where $S(T)_\mathrm{k}$ is the value of the $k^{th}$ cash flow path at time $T$ , $X$ is the exercise price at that time. In Equation(4.10) $-[r_f + \rho_{im} \frac{\sigma_i}{\sigma_m}(r_m - r_f)]$ is the calculated risk-adjusted rate for cash flows.

Thus the present value of the investment with option is given by:

$$O_0(T) = E\{S(T)_\mathrm{k}\, e^{-[r_f + \rho_{im} \frac{\sigma_i}{\sigma_m}(r_m - r_f)]T} - Xe^{-r_f T}\}^+ \qquad (4.11)$$

The expression for the value of flexibility/option is:

$$V_{option} = \max[\mathrm{O}_0(T) - V_0(T), 0] \qquad (4.12)$$

where $V_0(T)$ is the NPV of the investment without flexibility.

## 4.2.1 Valuation Process

This approach is generalized into three steps. First, a deterministic model with most likely design input variables (e.g. expected demand, price, cost, etc.) is constructed to estimate the cash flows in each time period using Excel®. If there are a variety of uncertain variables, a sensitivity analysis can be performed to select the important uncertain design variables. Next, uncertainty is incorporated into the Monte Carlo simulation model as several key random variables and the NPV of the whole design and the cash flow in each time period are estimated by discounting cash flows in the computed risk-adjusted discount rate. The last step is to incorporate identified real options into cash flow model by adding decision node in each exercising time period and comparing the present value of exercising an option or options with 0 at that time. Finally, the payoff distribution as well as the present value of real options can be obtained by summing up all the cash flows of the design with real options.

#### 4.2.1.1 Step 1: Create a Deterministic Cash Flow Model of the Initial Design without Flexibility and Identify Main Sources of Uncertainty

First of all, a model using excel spread sheet is created to estimate the cash flow stream for the initial design without flexibility under the deterministic projections of uncertainty (e.g. price, demand, cost, etc.) over the lifetime of the design. If there are more than one uncertain variable, a sensitivity analysis is conducted to determine how these variables affect the cash flows of the initial design. Three scenarios of random variables for the cash flow stream are estimated: the most likely or expected, the optimistic, and the pessimistic. By performing the sensitivity analysis, the significant random variables for the simulation in the next step are determined.

#### 4.2.1.2 Step 2: Incorporate Uncertain Variable(s) into the Model and Discount Cash Flows by Calculated Risk-Adjusted Rate

In this step, key uncertain variables (e.g. demand, price) are entered as simulation variables in the cash flow pro forma spreadsheet. To be consistent with classical option pricing model, the evolution of market related variables for cash flow calculation are assumed to follow a GBM process. The correlation coefficient of the market related variables and the market index are also estimated.

Key input parameters of random variables for the cash flow model can be determined by using as much market information as possible. First, the mean and variance of the market index return can be estimated from historical data of financial market. Next, the normal distribution of the market returns is approximated by a discrete distribution using the moment-matching methods (Miller and Rice 1983; Smith 1993) or the equal-area approach (McNamee and Celona 1987). Third, conditioning on each state and probability, the possible growth rate of each random variable on that state is estimated by the project manager. Finally, the mean and variance of random variables as well as their correlation with the market returns are estimated.

Once the input variables are determined, a Monte Carlo simulation is conducted to combine multiple sources of uncertainty into a single representative uncertainty: cash flow without option in each time period. Excel add-ins (e.g. RiskSim and @Risk) or more professional software (e.g. Crystal ball©) can be used to run the simulation easily. Then the present value (PV) of cash flow without option in each time period is discounted at the calculated risk-adjusted rate for that period. The PV of the project without option at each time period is the sum of the PV of all future cash flow till that time. Thus, the present value of the design without option at time 0 is obtained.

### 4.2.1.3 Incorporate Real Options and Evaluate the Value of these Options

The third step is to incorporate the identified flexibility by integrating simulation model with decision tree technique. Classical Monte Carlo simulation techniques for option pricing use continuous-time simulation to simulate the lognormal process of the underlying price movement, and valuate the option price at the exercise time. In the proposed cash flow simulation model, discrete-time observation of a GBM can be generated since a GBM is a Markov process. Thus decision nodes can be easily inserted in the exercising time to incorporate flexible design and management decisions into the model. The flexible decisions can be easily expressed by a logic function.

For instance, when there are no options, the formula for the present value $O_o(t, j)$ at time $t$, in path $j$ is given as:

$$O_0(t, j) = C_0(t, j) + \mathrm{O}_0(t + \Delta t, j)$$

where the present value $O_o(t, j)$ at time $t$ in path $j$ equals to the present value of cash flow received at that time plus the present value $O_0(t + \Delta t, \mathrm{j})$ in the next time period. When there is an option to abandon at time $t$ , the rollback PV of the abandon option in path $j$ is given by:

$$O_0(t, j) = \max[C_0(t, j) + \mathrm{O}_0(t + \Delta t, j), 0].$$

Thus the value of the abandon option is given by calculating the average of all simulated paths:

$$O_0(t) = E\{\max[C_0(t) + \mathrm{O}_0(t + \Delta t), 0]\}$$

## 4.2.2 Numerical Case Study

A numerical case is presented in this section to illustrate how the cash flow simulation model can be applied to the valuation of different real options. This case study evaluates an oil production project with multiple options in different time periods (Brandão, Dyer et al. 2005)

### 4.2.2.1 Problem Description

The problem which is utilized by Brandão, Dyer et al. to illustrate their binomial decision trees for real options valuation is an oil production investment problem. As stated in their paper, "the example project has estimated reserves of 90 million barrels and the initial production level of 9 million barrels declines by 15% per year over its 10-year operating life. The variable operating cost starts at $10 per barrel in Year 0 and grows at 2% per year. Oil price starts at $25 per barrel and grows at 3% per year. There is also a $5 million per year fixed cost that is not shown in the table. The appropriate risk-adjusted discount rate is assumed to be 10% per year, and the risk-free rate is 5% per year." The expected future cash flows are listed in Table 4-1.

**Table 4-1 Base case expected cash flows for the project in $ million (Brandão, Dyer et al. 2005)**

| Year | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Remaining reserves | | 90.0 | 81.0 | 73.4 | 66.8 | 61.3 | 56.6 | 52.6 | 49.2 | 46.3 | 43.9 |
| Production level | | 9.0 | 7.7 | 6.5 | 5.5 | 4.7 | 4.0 | 3.4 | 2.9 | 2.5 | 2.1 |
| Variable op cost rate | | 10.2 | 10.4 | 10.6 | 10.8 | 11.0 | 11.3 | 11.5 | 11.7 | 12.0 | 12.2 |
| Oil price | | 25.8 | 26.5 | 27.3 | 28.1 | 29.0 | 29.9 | 30.7 | 31.7 | 32.6 | 33.6 |
| Revenues | | 231.8 | 202.9 | 177.6 | 155.5 | 136.2 | 119.2 | 104.4 | 91.4 | 80.0 | 70.0 |
| Production cost | | (96.8) | (84.6) | (74.0) | (64.8) | (56.9) | (50.0) | (44.0) | (38.8) | (34.3) | (30.4) |
| Cash flow | | 135.0 | 118.3 | 103.6 | 90.7 | 79.3 | 69.2 | 60.4 | 52.6 | 45.7 | 39.6 |
| Profit sharing | | (33.7) | (29.6) | (25.9) | (22.7) | (19.8) | (17.3) | (15.1) | (13.1) | (11.4) | (9.9) |
| Net cash flows | | 101.2 | 88.7 | 77.7 | 68.0 | 59.5 | 51.9 | 45.3 | 39.4 | 34.3 | 29.7 |
| PV of cash flows | 404.0 | 444.5 | 377.6 | 317.7 | 264.0 | 215.6 | 171.7 | 131.8 | 95.1 | 61.3 | 29.7 |
| Cash flow payout rate | | 0.228 | 0.235 | 0.245 | 0.258 | 0.276 | 0.302 | 0.344 | 0.414 | 0.559 | 1.000 |

The time step $\Delta t$ is one year. The initial expected net present value (ENPV) of the underlying project calculated by a deterministic discounted cash flow (DCF) model is \$404.0 million. The volatility $\sigma$ determined by using this DCF model and a Monte Carlo simulation is 46.6% per year. A binomial tree is used to approximate the GBM process of the underlying value.

In Year 5, there are three alternatives in the project: (1) option to divest for a price of \$100 million; (2) option to buy out the partner's 25% share for \$40 million; and (3) option to continue as before. Decision nodes are added in the tree to evaluate the ENPV of the project with these real options, which is \$444.9 million.

To incorporate private uncertainty into the model, the authors suppose that from Year 6 to Year 10 which is the end of the project's life, there will be a risk that the drilling machines may reach an underlying aquifer and they will begin producing water, and operations should be shut down. This private risk is uncorrelated with any market return. Two additional options are considered: option to continue or to shut down the operations. This uncertainty reduces the ENPV of the project to \$428.0 million.

However, Smith points out that the volatility of project's initial ENPV is overestimated in BDH approach since the calculated volatility is the cumulative outcome of all future uncertainties over project's operating lifetime, not the actual volatility during 1 unit of the time step ( $\Delta t = 1$ ) (Smith 2005). By searching he also suggests a volatility of 25.5% per year would fit the original cash flow model much better, although still not perfect.

#### 4.2.2.2 Solutions Using the Proposed Risk-adjusted MC-DT Approach

For this example, instead of using an exogenously specified risk-adjusted discounted rate for the cash flow model, key random variables (i.e. operating cost and oil price) are assumed to correlate with a market-traded asset. The long-term market returns of the market index are assumed to be normally distributed with a mean of 10% and a volatility of 20%. The correlation among this market return, operating cost and oil price can be determined by moment-matching methods (Miller and Rice 1983; Smith 1993) or the equal-area approach (McNamee and Celona 1987). For the illustration purpose, it is first assumed that the operating cost and oil price are both perfectly positively correlated with the market return, thus $\rho = 1$. In this case, the market is complete.

Figure 4-1 displays the risk-adjusted cash flow model for the evaluation of real options. Rather than approximated by a simple univariate, the stochastic process of cash flow and project value can be directed generated by simulating multiple random variables such as oil prices and variable operating cost. From the following cash flow model, we can obtain an estimated volatility 20% for net cash flow per year, which is the same as the assumed volatility of market returns. The calculated correlation between the net cash flow and the market return in each year is 1. This is identical to the theatrical value, since the random variables are all perfectly positively correlated with the market return. Therefore, the calculated risk-adjusted discounted rate is 10%, thus equalling to the one assumed in BDH approach. The ENPV of the project without real options is $401 million, slightly different from the one calculated in BDH approach since the discounted factor in the proposed model is computed in geometric instead of arithmetic form.

| | A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | risk-free rate | 5% | | | | fix cost | $ 5 | | | | | |
| 2 | assumed risk-asjusted rate | 10% | | | | | | | | | | |
| 3 | growth rate of oil price | 3% | σ_p | 15% | SD_p | 0.3873 | | | | | | |
| 4 | growth rate of operating cost | 2% | σ_oc | 10% | SD_oc | 0.31623 | | | | | | |
| 5 | market rate of returns | 0.1 | σ_rm | 20% | SD_rm | 0.44721 | | | | | | |
| 6 | | | | | | | | | | | | |
| 7 | | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| 8 | Remaining reserves | | 90 | 81 | 73.3 | 66.8 | 61.3 | 56.6 | 52.6 | 49.2 | 46.3 | 43.8 |
| 9 | Production level | | 9 | 7.7 | 6.5 | 5.5 | 4.7 | 4 | 3.4 | 2.9 | 2.5 | 2.1 |
| 10 | Variable op cost rate | 10 | 9.7 | 9.4 | 9.1 | 8.9 | 8.6 | 8.4 | 8.1 | 7.9 | 7.6 | 7.4 |
| 11 | Oil price | 25 | 23.9 | 22.8 | 21.8 | 20.9 | 20.0 | 19.1 | 18.2 | 17.4 | 16.7 | 15.9 |
| 12 | Marginal profit | 15.0 | 14.2 | 13.4 | 12.7 | 12.0 | 11.4 | 10.7 | 10.1 | 9.6 | 9.0 | 8.5 |
| 13 | Market Risk | 1 | 1.1 | 1.2 | 1.3 | 1.5 | 1.6 | 1.8 | 2.0 | 2.2 | 2.5 | 2.7 |
| 14 | σ_market risk | | 20% | 40% | 61% | 82% | 105% | 125% | 148% | 178% | 199% | 212% |
| 15 | Revenues | | 215.1 | 175.9 | 142.0 | 114.8 | 93.8 | 76.3 | 62.0 | 50.6 | 41.7 | 33.5 |
| 16 | Production cost | | $ (92.34) | $ (77.52) | $ (64.41) | $ (53.78) | $ (45.45) | $ (38.41) | $ (32.56) | $ (27.81) | $ (24.08) | $ (20.56) |
| 17 | Cash flow | | 122.8 | 98.4 | 77.6 | 61.1 | 48.4 | 37.9 | 29.5 | 22.8 | 17.6 | 12.9 |
| 18 | Profit sharing | | $ (30.7) | $ (24.6) | $ (19.4) | $ (15.3) | $ (12.1) | $ (9.5) | $ (7.4) | $ (5.7) | $ (4.4) | $ (3.2) |
| 19 | Net cash flows | 0 | 92.1 | 73.8 | 58.2 | 45.8 | 36.3 | 28.4 | 22.1 | 17.1 | 13.2 | 9.7 |
| 20 | σ_net cash flow | | 20% | 40% | 61% | 81% | 103% | 123% | 145% | 171% | 191% | 206% |
| 21 | Crrelation between market risk and cash flow | | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| 22 | PV of cash flows | 282.7 | 312.5 | 243.6 | 187.6 | 143.1 | 107.5 | 78.7 | 55.5 | 37.0 | 22.0 | 9.7 |
| 23 | risk-ajusted rate | | 10% | 10% | 10% | 10% | 10% | 10% | 10% | 10% | 10% | 10% |
| 24 | NPV of cash flows | | 83.3 | 60.4 | 43.1 | 30.7 | 22.0 | 15.6 | 11.0 | 7.7 | 5.4 | 3.6 |
| 25 | NPV of project without flexibility | | 282.7 | 199.4 | 139.0 | 95.9 | 65.2 | 43.2 | 27.6 | 16.6 | 8.9 | 3.6 |
| 26 | ENPV without flexibility | | 401 | | | | | | | | | |
| 27 | NPV of project with flexibility | | 300.2 | 216.9 | 156.5 | 113.4 | 82.7 | 43.2 | 27.6 | 16.6 | 8.9 | 3.6 |
| 28 | ENPV with flexibility | | 440.9 | | | | | | | | | |

**Figure 4-1 A risk-adjusted cash flow simulation model for the oil production Example (Brandão, Dyer et al. 2005)**

In Year 5, three alternative decisions can be expressed by:

$$
\begin{aligned}
O_0(t, j) = \max\{ & C_0(t, j) + \mathrm{O}_0(t+\Delta t, j), \\
& C_0(t, j) - \$40 + \frac{4}{3}\mathrm{O}_0(t+\Delta t, j), \\
& C_0(t, j) + \$100 \}
\end{aligned}
\tag{4.13}
$$

where the three terms correspond to the payoff of three decisions: option to continue, option to pay $40 million to buy out the partner’s 25% share thus gaining 4/3 of the expected future value, option to sell your share for $100 million. The Excel logic functions are used to return the distributions of maximum in all simulated paths. The ENPV of the project with flexibility is increased to $440.9 million.

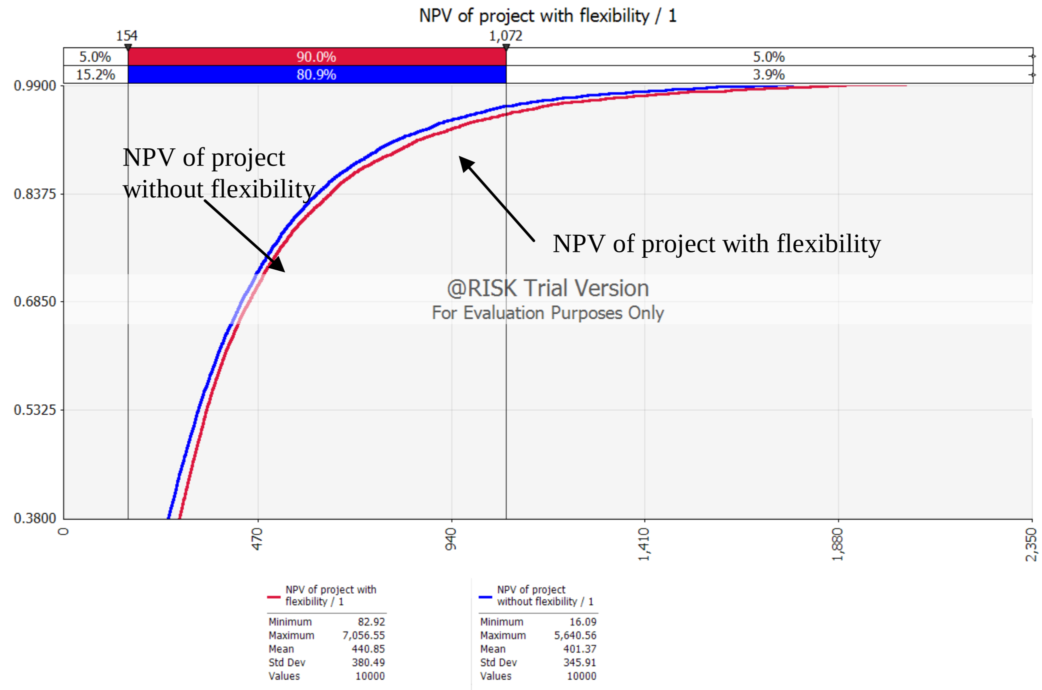



**Figure 4-2 Cumulative distributions of NPV for project with and without flexibility**

Figure 4-2 displays the cumulative probability distributions (CPD) of NPV for the project with and without flexibility. It shows that by incorporating flexibility into the project, the CPD of project's NPV shifts to the right, which means that the potential downside risks are limited and possible upside opportunities are explored by making optimal flexible decisions.

If the correlations between market returns and oil price as well as operating cost are $\rho_{mp} = 0.8$ and $\rho_{mc} = 0.6$ respectively[4], the computed risk-adjusted discount rate is decreased to 7%, the ENPV of the project without flexibility is \$447 million and the ENPV of the project with flexibility is \$516.1 million. The ENPVs are increased since the correlation between market return and the cash

[4] In fact, since oil is traded in the market, if the oil stock is chosen as the market asset, it is always perfectly positively correlated with the oil price, but for demonstration purpose, I assume that they are partially correlated, it is reality when the market is incomplete which the underlying asset is not traded in the market and is partially correlated with a traded asset.

flow is decreased, and the private risks which are uncorrelated with market return are discounted in risk-free rate.

## 4.3 Summary

The proposed approach augments and extends DM method (Datar, Mathews et al. 2007) by integrating the cash flow simulation model with decision tree technique. The advantages of the proposed risk-adjusted cash flows simulation based approach are listed as follow.

First of all, it is practically implementable. Decision tree can be integrated in each discrete time period. Therefore valuing various options (e.g. multiple options, compound options and American option) can be valued by encoding relevant rules at each decision node.

Second, it is consistent with financial theory. Financial theory the motion of the uncertainty is path dependent. In DM method, cash flows in different time periods are assumed to follow triangular distribution and are not naturally correlated. The DM method requires a subjective estimation of correlation matrix based on historical data. However, in practices, especially for projects with new technologies, such information is hard to obtain. While the proposed approach use a discrete time approximation of GBM to simulate cash flows in different time period. The Markov process of the discrete time GBM captures the path dependence of cash flows between two periods. Moreover, the approach properly accounts for both systematic and project-specific risks by risk adjusting the cash flow based on CAPM model, and thus it is able to provide a correct valuation from a diversified invertors’ viewpoint.

Third, it uses market information as much as possible. Rather than exogenously estimating a risk-adjusted rate in DM method, market information such as a probability distribution of a market traded asset correlated with the cash flows and the possible return estimation of the cash flow conditional on different market returns of the traded asset are used to calculate the risk-adjusted discount rate.

In addition, comparing with lattices and tree widely used in practical ROV methods, the cash flow simulation based model can incorporate multiple source of uncertainty without suffer from "curse of dimensionality", and provides not only the mean value but also probability distribution of the option payoffs, which provides more insight on the risk and gain of the design value with flexibility.

# 5 Case Study: Embedding Flexibility in Unmanned Aerial Vehicle System Design

## 5.1 Introduction

In previous chapters, a framework which integrates two novel approaches has been proposed to design and manage flexible engineering systems under complex interactions of environmental uncertainties and system architectures. The purpose of this chapter is to demonstrate the application of the two proposed methodologies in a design study for a hypothetical commercial Unmanned Aerial Vehicles (UAV) manufacturing project development.

This chapter starts with a description of UAV systems and the opportunities and challenges for UAV system designers and manufacturers, followed by the demonstration the proposed two-stage real options framework. The first stage of the framework applies the proposed screening process and matrix-based simulation approach to determine the most potential areas for embedding flexibility. The second stage of the framework uses the proposed cash flow simulation-based approach to value and select real options identified in UAV and provide the optimal staged deployment strategies over the lifetime of the UAV manufacturing project.

## 5.2 Background

UAVs are remotely piloted or self-piloted aircraft that can carry various payloads (e.g. cameras, sensors, communications equipment,etc). They can play the same roles as manned aircrafts, but they are often more cost-effectively and more preferred for the “dull, dirty or dangerous” missions.


**Figure 5-1 UAV system**

Generally, a UAV system consists of three main parts: the air vehicle, the ground control station and the operator (as shown in Figure 5-1). Only the air vehicle and the ground control station are analyzed in this case study, for simplifying the discussions. The air vehicle includes all subsystems within the physical airframe, including the airframe itself and all interior avionics. A ground control station (GCS) is a land- or sea-based control center that provides the facilities for human control of UAV. It contains two subsystems: ground station to carry equipments (e.g. a laptop computer and the GCS hardware), and the operator control unit which is a software system providing a graphical user interface. To simplify the discussions, this research only considers flexibility in hardware subsystems to maintain or enhance system lifecycle value under uncertainty. However the methodology can be extended to include flexibility in software system (e.g modularizes software for easy upgrading).

UAVs are capable of performing a wide range of missions. Currently, the majority of these functions are primarily set to fulfill military and special operation applications, mainly for the purposes of intelligence, surveillance and reconnaissance (ISR). "UAVs are 99 percent ISR today, they need to be multipurpose – ISR and target acquisition, aerial network layer, attack capabilities, sustainment and cargo", said Glenn Rizzi, deputy director at the Army Unmanned Aerial Systems Center of Excellence, USA. With the increasing used in the civilian applications (e.g. such as earth observation for scientific research, coastal patrol for homeland security, forest fire damage assessment) and evolving customer requirements, UAVs are required to fulfill a greater scope of functional requirements.

Although the growing demand for UAVs in civilian applications provides an opportunity to commercial UAVs manufacturers, it is also a challenge since the long-term demand of UAVs is greatly affected by various technical, economical and political uncertainties. For instance, the fast evolution of aerospace technologies can not only provide new functions in UAVs but may also lower the manufacturing cost of new UAVs. Therefore some customer needs will shift towards new UAVs. If the existing UAV platform will not be able to adopt the new technologies with relative ease, it may become obsolescence, thus causing a large amount of lost in capital investment.

Historically, due to the high requirements in military applications, various UAVs platforms have been customized to satisfy a specific or a small range of military purposes via optimization technique. This requires significant capital investments for independent R&D efforts and individual manufacturing lines, thus resulting high-cost UAV applications. However, when UAVs are applied for civilian uses, customers require less expensive UAV. Suppose currently, UAVs with basic functions are sufficient to fulfill the daily missions of the customers. However, suppose that there will be a growing demand for UAV which is able to perform more missions with higher functional requirements. The customized platforms are expensive and difficult to adapt to changes in missions once built and deployed. On the contrary, flexible platforms are able to accommodate emerging technology innovation and rapidly changing customer needs with relatively low cost. For instance, a flexible UAV is designed with interchangeable wings and corresponding interfaces on the fuselage. This will allow the UAV to achieve different speed requirements, thus providing a constant high performance with fewer penalties (i.e. cost, time) during its lifetime.

To maximize profits under uncertainty, UAV system designers and manufacturers should consider the potential to embed flexibility/real options in UAVs manufacturing. The flexibility is incorporated via flexible product platform strategy. Flexible product platform strategy is a widely used as staged deployment strategy in many high-technological industries (e.g. automobile and aircraft manufacturing). It begins with a platform design to meet current requirements of the stakeholder with relatively low capability, but also provides the opportunities to modify or replace the flexible subsystems for higher capability with relatively low cost. However, it is difficult to identify, value, and manage appropriate real options "in" a UAV system due to multiple uncertainties which affect the UAV performance and demand, the complexities of system architecture, and the risks associated with the additional investment cost of flexibility. This case study aims to develop a flexible UAV platform which can maintain or improve system lifetime value by adapting to multiple future uncertainties. The following sections provide a description on how to embed flexibility in UAV manufacturing project utilizing real options.

## 5.3 Identify Real Options "in" System

This section screens the critical subsystems where system designers should place more efforts to incorporate flexibility and robustness.

### 5.3.1 Step 1: Identify System Purpose and Critical Mission(s)

The purpose of the UAV manufacturing project is to design and produce civilian UAVs for multiple mission applications. The mission profiles of UAVs are determined by identifying current and possible future customer needs. The mission requirements are then decomposed into a set of functional requirements (FRs). Important FRs for mission performance characteristics are specified in payload, range, endurance, typical operating and maximum altitude, cruise and maximum speed, etc. Different missions require different combinations of performance specifications. For example, a city patrol mission requires long endurance (> 24 hours), and does not have a high cruise or dash speed. Agricultural missions such as crop-spraying, seeding, and remote sensing, require a UAV to carry heavy payload, and do not require a long range. A typical agricultural UAV – Yamaha's RMAX can carry a 28 kg payload and has 2 km operational range.

Suppose the original UAV is designed for personal "over the hill" reconnaissance mission. However, in the near future, the customers may require a UAV incapable of (1) searching for survivors from shipwrecks, aircraft accidents etc; (2)

detecting wild fire on a large area of forest; (3) street loitering, inspection and patrol.

### 5.3.2 Step 2: Identify Main Sources of Uncertainty and Change Scenarios

Like many other complex engineering systems, the design and development of a UAV system are constantly facing three major sources of uncertainty: dynamic market place, evolving technologies and changing operation environment. For each source of uncertainty, a change scenario is assumed below:

1. A change in payload due to the innovation in sensor technology. Suppose a new sensor technology will be able to provide both day and night imaging. The new sensor can be applied in the search and rescue mission to enhance the searching performance.

2. A change in range due to the changing environment when performing the mission of wild fire suppression. The area of forest may be large than current expectation, thus requiring a UAV to fly a longer range to detect the fire spot.

3. A change in endurance due to customer demand. Suppose there will be a growing need for UAV patrolling to assist the daily mission of police.

Each change scenario is weighted by the product of the probability $p_s$ that the change will occur in the future and its opportunity $O_s$ which quantifies the impact of the change scenario on system's LCV.

Table 5-1 lists the $p_s$ and $O_s$ for each change scenarios consider in this case study.

**Table 5-1 The probabilities and opportunities of change scenarios**

| Change Scenario (*CS*) | $p_s$ | $O_s$ |
|---|---|---|
| Payload ($CS_1$) | 0.6 | 0.8 |
| Range ($CS_2$) | 0.4 | 0.6 |
| Endurance ($CS_3$) | 0.8 | 0.8 |

### 5.3.3 Step 3: Determine an Initial Design and Value Assessment

The baseline design was designed to satisfy the originally intended purpose of the system without considering future uncertainties. It is capable to perform the mission of "over the hill" reconnaissance in this case study. The value of the baseline is measured in monetary form in order to be consistent with the real options valuation methods proposed in Chapter 0. Flexibility of the system is then measured by comparing to value of the original design.

### 5.3.4 Step 4: Develop System Representation and Access Change Dependency

The UAV system is represented by an ESM which comprises three DSMs and the corresponding DMMs. The DSMs are system drivers DSM, functional requirements DSM and subsystems DSM. The changes in system drivers (described by change scenarios) propagate to subsystems via changes in functional requirements. Each change scenario is supposed to map to a change in a unique functional requirement. To simplify the representation, only the change relationships of system drivers (SDs) to subsystem and subsystem to subsystem are presented in an extend DSM.

Table 5-2 lists the main subsystems of a fixed wing UAV (Musial 2008; Hamraz, Caldwell et al. 2012)). Recall in Section 3.3.4, the subsystem directly affected by external changes is called as a change initiator. The identified change initiators for each change scenario are presented in Table 5-3 (Raymer 2006; Wilds 2008). The magnitude of a change in one subsystem caused by a change in other subsystems or system drivers (external changes) is quantified by the product of probability and the corresponding change impact. The direct likelihood and impact matrices including critical links are shown in Figure 5-2 and Figure 5-3 respectively.

**Table 5-2 Subsystems of a fixed wing UAV**

| | | | | | |
|---|---|---|---|---|---|
| 1. Wing | 2. Empennage | 3. Propeller | 4. Fuselage | 5. Transmission | 6. Sensor |
| 7. Camera | 8. Micro Controller | 9. Data Transmitter | 10. Video Transmitter | 11. Antenna | 12. Autopilot |
| 13. Battery | 14. Motor | 15. Battery Charger | 16.Parachute | 17. Auxiliary Electrics | 18. Ground Station |

**Table 5-3 Identified change initiators for each change scenario**

| Change Scenario | Change Initiator(s) |
|---|---|

| | |
|---|---|
| Payload ( $CS_1$ ) | 6. Camera<br>7. Sensor |
| Range ( $CS_2$ ) | 9. Data Transmitter<br>11. Antenna |
| Endurance ( $CS_3$ ) | 1. Wing<br>3. Propeller<br>13. Battery<br>14. Motor |

| | | SD | | | Subsystem | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
| SD | 1 | | | | | | | | | | | | | | | | | | | | | |
| | 2 | | | | | | | | | | | | | | | | | | | | | |
| | 3 | | | | | | | | | | | | | | | | | | | | | |
| Subsystem | 1 | | | 40 | | | | 20 | | | | | | | | | | | | | | |
| | 2 | | | | 70 | | | | | | | | | | | | | | | | | |
| | 3 | | | 20 | 20 | | | | 20 | | | | | | | 20 | | | | | | |
| | 4 | | | | 20 | 20 | 20 | | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | 20 | | | |
| | 5 | | | | 20 | 20 | 20 | | | | | | | | | 20 | | 60 | | | | |
| | 6 | 80 | | | | | | | | | | | | | | | | | | | | |
| | 7 | 100 | | | | | | | | | | | | | | | | | | | | |
| | 8 | | | | | | | | 20 | 60 | 60 | | | | | 50 | 20 | 80 | | | | |
| | 9 | | 20 | | | | | | | 50 | 20 | 20 | | | 20 | | | | | | | |
| | 10 | | | | | | | | | | 50 | 20 | | | 20 | | | | | | | |
| | 11 | | 80 | | | | | 20 | | | | | | | | | | | | | | |
| | 12 | | | | 20 | | | | 20 | | | | | | | | | 20 | | | | |
| | 13 | | | 80 | | | | 50 | | 50 | 60 | | | | | | | 80 | | | | |
| | 14 | | | 80 | | | | 50 | | | | | | | | | | | | | | |
| | 15 | | | | | | | | | | | | | | | | | | | | | |
| | 16 | | | | | | | 20 | | | | | | | | | | | | | | |
| | 17 | | | | | | | 60 | 20 | 0 | 20 | 20 | 20 | 20 | | 60 | | 20 | 20 | | | |
| | 18 | | | | | | | | | | | | 20 | 20 | | | | | | | | |

**Figure 5-2 Likelihood DSM composed of system drivers to subsystem DMM and subsystem DSM (in %)**

| | | SD | | | Subsystem | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
| SD | 1 | | | | | | | | | | | | | | | | | | | | | |
| | 2 | | | | | | | | | | | | | | | | | | | | | |
| | 3 | | | | | | | | | | | | | | | | | | | | | |
| Subsystem | 1 | | | 80 | | | | 60 | | | | | | | | 0 | | | | | | |
| | 2 | | | | 20 | | | | | | | | | | | 0 | | | | | | |
| | 3 | | | 40 | 20 | | | | 20 | | | | | | | 20 | | | | | | |
| | 4 | | | | 60 | 20 | 20 | | 20 | 20 | 20 | 20 | 20 | 20 | 10 | 20 | 60 | 60 | 20 | | | |
| | 5 | | | | 20 | 20 | 20 | | | | | | | | | 20 | | 20 | | | | |
| | 6 | 60 | | | | | | | | | | | | | | | | | | | | |
| | 7 | 60 | | | | | | | | | | | | | | | | | | | | |
| | 8 | | | | | | | | 20 | 20 | 20 | | | | | 20 | 20 | 20 | | | | |
| | 9 | | 10 | | | | | | | 10 | 10 | 10 | | | 10 | | | | | | | |
| | 10 | | | | | | | | | | 20 | 20 | | | 20 | | | | | | | |
| | 11 | | 20 | | | | | 10 | | | | | | | | | | | | | | |
| | 12 | | | | 20 | | | | 20 | | | | | | | | | 20 | | | | |
| | 13 | | | 20 | | | | 20 | | 20 | 20 | | | | | | | 20 | | | | |
| | 14 | | | 40 | | | | 60 | | | | | | | | | | | | | | |
| | 15 | | | | | | | | | | | | | | | | 10 | | | | | |
| | 16 | | | | | | | 20 | | | | | | | | | | | | | | |
| | 17 | | | | | | | 10 | 10 | | 10 | 10 | 10 | 10 | | 10 | | 10 | 10 | | | |
| | 18 | | | | | | | | | | | | 20 | 20 | | | | | | | | |

**Figure 5-3 Impact DSM (in %)**

# 5.3.5 Step 5: Predict Change Propagation Impacts Using Proposed Matrix-Based Simulation Approach

## 5.3.5.1 Identify and Remove Cycle-Causing Edges

Before calculating the change prediction, the edges which cause cycles in the change propagation network and the associated elements are identified and removed using the proposed algorithm. Without drawing the DG which includes 18 nodes and the complex edges between nodes, the proposed algorithm is able to identify and remove the cycle-causing edges as late as possible. For instance,

Figure 5-4 displays the cyclic paths among subsystem **3**, **5**, **12**. The edges $5 \to 3$, $12 \to 3$ and $12 \to 5$ are removed and recorded by the proposed algorithm.

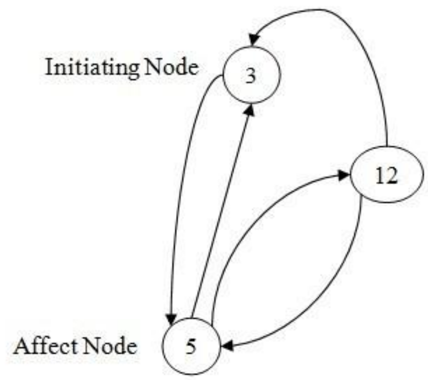



**Figure 5-4 Cyclic paths among subsystem 3,5,12**

#### 5.3.5.2 Change Propagation Analysis

The proposed matrix-based simulation algorithm is applied to analysis the change propagation probabilities and risks on subsystems due to multiple environmental uncertainties. Two indicators are calculated to measure the change propagation impacts. The environmental impact-received (*EI-R*) of a subsystem is a measure of how each subsystem is affected by all identified environmental uncertainties. The Internal Impact-Supply (*II-S)* of a subsystem is a measure of how the subsystem influences others if it is required to be changed in response of environmental uncertainties. Table 5-4 displays the calculated indicators of all the subsystems.

**Table 5-4 EI-R and II-S of subsystems**

| Subsystem | II-S | EI-R |
|---|---|---|
| 1 | 0.4 | 0.19 |
| 2 | 0.07 | 0.15 |
| 3 | 0.08 | 0.13 |
| 4 | 0.41 | 0.71 |
| 5 | 0.19 | 0.27 |
| 6 | 0.83 | 0.51 |
| 7 | 0.97 | 0.64 |
| 8 | 0.48 | 0.88 |
| 9 | 0.13 | 0.44 |

| Subsystem | II-S | EI-R |
|---|---|---|
| 10 | 0.12 | 0.31 |
| 11 | 0.17 | 0.29 |
| 12 | 0.11 | 0.15 |
| 13 | 0.51 | 0.82 |
| 14 | 0.92 | 0.38 |
| 15 | 0.02 | 0.13 |
| 16 | 0.03 | 0.14 |
| 17 | 0.12 | 0.75 |
| 18 | 0.03 | 0.13 |

## 5.3.6 Identify Critical Subsystems for Flexibility and Robustness

Figure 5-5 portrays the two indicators $EI-R$ and $II-S$ of each subsystem as orthogonal dimensions.

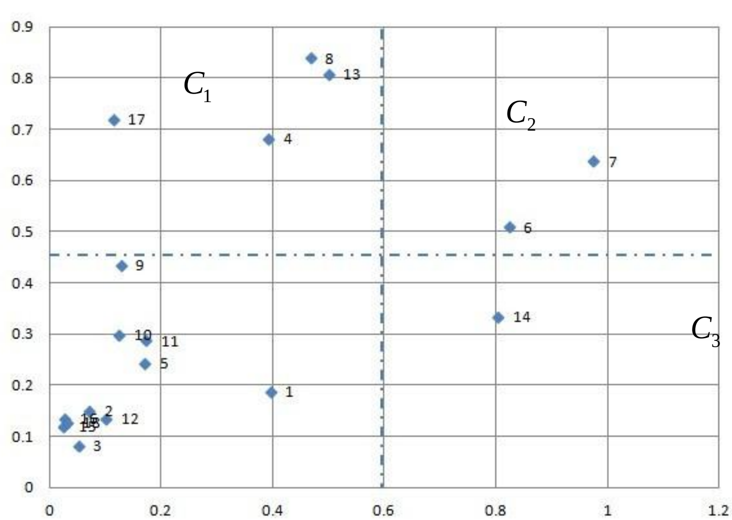



**Figure 5-5 Classification of subsystems in UAV**

The following subsystems are identified for flexibility:

1. Subsystems with high EI-R and high II-S are the primary candidates for flexibility. The subsystem 6 (sensor) and 7 (camera) are considered as promising areas for embedding flexibility. They are likely changed in response to high degree of environmental uncertainties. Actually they are directly influenced by future change scenario in technology sensor for day and night image. This change scenario has a relatively high probability and opportunity. They also cause relative high impact on the system. The impact/switch cost of the sensor and camera are relatively high (60% of estimated direct impact caused by $CS_1$). To reduce the switch cost, sensor and camera subsystems should be modulated thus providing real options to for easily modifying or replacing in the future.
2. Subsystems 8 and 13 with high EI-R is also recommended as flexible candidates. Subsystem 8 (Avionics) is not directly influenced by change scenarios. However, due to the indirect effect, its EI-R is relatively high, thus it is very likely to be changed in response to external changes. It also has a medium II-S, mainly caused by its high switch cost. Subsystem 13 (battery) is very likely to be changed due to future change in endurance and by other subsystems. To enable possible change with relatively low cost, avionics and battery subsystems should be modulated.

The following subsystems are identified for robustness

1. Although Subsystem 4 (Fuselage) has a high EI-R, a change in fuselage will cause a high cyclic effect due to the many cyclic-causing edges from

fuselage to other subsystems. Thus it should be made insensitive to change (robustness) by increasing its change margin.

2. Subsystem 14 (motor) has relatively low EI-R but high II-R. A change in 14 is likely to cause high switch cost more changes in other subsystems. Therefore it should be insensitive to change.

# 5.4 Evaluate Real Options "in" System

## 5.4.1Design Alternatives

In Section 5.3.6 four subsystems identified for embedding flexibility: camera, sensor, avionics, and battery. Several assumptions simplifying the calculation are considered to emphasize the valuation process.

The UAV manufacturers consider three design alternatives:

1. Fixed platform 1 which produces basic UAV1 to meets current customer's requirement.
2. Fixed platform 2 which produces enhance UAV2 with flexible battery bay.
3. A flexible platform 3 which is able to produce basic UAV1 and enhances endurance UAV2 with flexible battery bay.

The manufacturer only chooses to one type of platform: 1, 2 or3. Each platform has a capacity limit at 2000 UAV per year. A flexible platform is able to produce the more valuate product first if the demand exceed the capacity. A 10-year period is considered: the manufacturer launch the project at year 0. They are able to produce UAV1 which meet the basic requirement at year 1, UAV2 which meet the enhance endurance at year 2 due to the technical difficulty. Table 5-5 list the cost for each product platform. Table 5-6 provides the market information of the demand. It is assumed that the demands for UAV 1 and UAV2 are correlated with a market index with a mean 10% and volatility 15%.

**Table 5-5 Different types of UAV cost**

| Platform Type | Fixed 1 | Fixed 2 | Flexible |
|---|---|---|---|
| Launch Cost | $10,000 | $15,000 | $20,000 |
| Fixed Cost | $1.5M | $1.75M | $1.95M |
| Marginal Cost | $2000 per UAV | $2200 per UAV | $2500 per UAV |
| Price | $7000 basic | $10000 enhance endurance | $7000 basic<br>$10000 enhance endurance |

**Table 5-6 Demand Information**

| | UAV 1 | UAV 2 |
|---|---|---|
| Forecast Demand | 600 at year 1 | 500 at year 2 |
| Growth Rate | 10% | 13% |
| Volatility | 15% | 15% |

## 5.4.2Result

**Table 5-7 Simulation result**

| Year | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 600 | 714.74773 | 851.44 | 1014.28 | 1208.25 | 1439.33 | 1714.59 | 2042.50 | 2433.12 |
| | | 600 | 714.74773 | 851.44053 | 1014.2753 | 1208.2516 | 1439.3252 | 1714.5907 | 2000 | 2000 |
| | | 1,500 | 2,074 | 2,757 | 3,571 | 4,541 | 5,697 | 7,073 | 8,712 | 10,666 |
| Fixed 1 | 15135.84 | 1357.26 | 1697.83 | 2042.59 | 2393.97 | 2754.41 | 3126.37 | 3512.32 | 3914.78 | 4336.31 |
| | | | | | | | | | | |
| | | 0 | 500 | 613.76 | 753.41 | 924.83 | 1135.25 | 1393.55 | 1710.61 | 2099.82 |
| | | | 200 | 613.76 | 753.41 | 924.83 | 1135.25 | 1393.55 | 1710.61 | 2000.00 |
| | | | 1500 | 4603.219 | 5650.5667 | 6936.2122 | 8514.3744 | 10451.608 | 12829.611 | 15748.669 |
| Fixed 2 | 19663.507 | | 1228.0961 | 3410.1485 | 3787.6881 | 4207.0254 | 4672.7877 | 5190.1149 | 5764.7157 | 6402.9309 |
| | | | | | | | | | | |
| | | 600 | 714.74773 | 851.44 | 1014.28 | 1208.25 | 1439.33 | 1714.59 | 2042.50 | 2433.12 |
| | | 0 | 500 | 613.76 | 753.41 | 924.83 | 1135.25 | 1393.55 | 1710.61 | 2099.82 |
| | | 600 | 1214.7477 | 1465.20 | 1767.68 | 2133.08 | 2574.58 | 3108.14 | 3753.11 | 4532.94 |
| | | 0 | 500 | 613.76 | 753.41 | 924.83 | 1135.25 | 1393.55 | 1710.61 | 2000.00 |
| | | 600 | 714.74773 | 851.44 | 1014.28 | 1075.17 | 864.75 | 606.45 | 289.39 | 0.00 |
| | | 2700 | 6966.3648 | 8434.7014 | 10214.806 | 11774.485 | 12405.75 | 13180.643 | 14131.844 | 15000 |
| Flexible | 34,186.12 | 2,443.06 | 5,703.58 | 6,248.58 | 6,847.19 | 7,141.59 | 6,808.42 | 6,545.31 | 6,349.85 | 6,098.54 |

By using the proposed risk-adjust MC-DT approach, the ENPV of each platform is shown in Table 5-7. It shows that the flexible product platform has the highest ENPV. The cumulated distribution NPV for each platform is displayed in Figure 5-6.

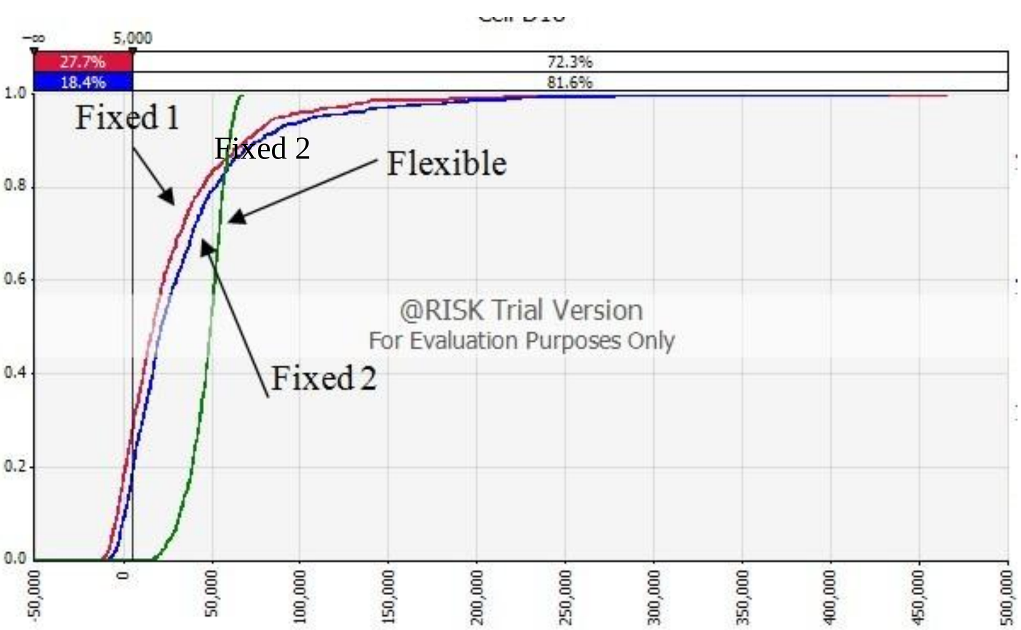



**Figure 5-6 CDF of NPV for each platform**

# 6 Conclusions and Future Work

## 6.1 Summary

This thesis introduces a framework and methodology to improve the live-cycle value of engineering systems which require intensive capital investment, are difficult to change once fielded due to complex interconnections among subsystems, and operate under multiple sources of uncertainty for a long time period (e.g. 10 years, 20 years and even longer). Flexibility is embedded in engineering systems to provide options to expand, contract, switch, improve, or modify the identified flexible elements, thus taking advantage of upside opportunities and avoiding downside risks.

A two-step framework with two distinct but complementary approaches is developed to design and manage real options "in" complex engineering system. Chapter 3 presents a systematic six-step screening process to screen a system for locating the promising system elements for real options in the stage of real option identification. Firstly, a matrix-based simulation approach is proposed and utilized to analyze the change propagation behaviors and impacts of subsystems due to multiple sources of uncertainty. Secondly, two indicators, which measure the change propagation impact of a subsystem received and supply to others, are proposed. Based on the two proposed indicators and the identified cycle-causing subsystems, comprehensive recommendations are proposed to identify flexible subsystems and insensitive (robust) subsystems.

Chapter 4 presents a practically implementable and theoretically consistent valuation approach to assess the value of the embedded options with the objective of selecting the best combination of real options and determining the optimal timing to exercise the real options. The proposed risk adjusted MC-DT approach integrates Monte Carlo simulation and decision tree techniques. Numerical simulations have been conducted to demonstrates the effectiveness of the proposed approach.

Chapter 5 presents a case study of UAV manufacturing project. Both the six-step screening process proposed in Chapter 3 and the risk adjust MC-DT approach proposed in Chapter 4 are applied. The simulation results have indicated the effectiveness of them.

## 6.2 Contribution

This thesis proposed a systematic framework for designing flexibility in engineering systems under multiple uncertainties. The specific contributions are:

1. A novel change propagation prediction method based on simulation is proposed. The advantage of the proposed method is that it avoids “brutal-force” searching, and thus it is less computational intensive compared to those in the literature. This renders it easily implementable for engineering practices. Another main advantage is that it allows analysis of change propagation effects under multiple changes while the existing methods only allow single change.
2. A comprehensive six-step screening process is proposed. The main merit of the proposed screening process is that both the direct and indirect impacts of change propagation under multiple uncertainties in the operational environments are considered. Moreover, cyclic effects of change propagation are identified and recommendations for how to eliminate them are proposed. Two indicators, “EI-R” and “II-S”, are proposed to facilitate the

measurement of the combined effects of direct and indirect change propagation.

3. A practically implementable and theoretical consistent real option valuation approach is proposed. The key advantage of this proposed valuation approach is that it is able to incorporate multiple sources of uncertainty. Another key advantage is that it is able to evaluate various types of real options and provide statistic results for further risk analysis. Moreover, it only requires minimal subjective estimation of input parameters. Furthermore, the proposed approach is consistent with financial theories since it considers both systematic and project-specific risks by risk adjusting the cash flow based on CAPM model.

# 6.3 Future Work

There are several interesting directions for future work in the areas of real options. Ones of the most important future directions is in the field of real option management (as shown in Figure 6-1). In the management stage, system states should be constantly monitored. The monitor step not only provides information for system designers to determine whether and when to exercise the options, but also provides feedback for previous stages, thus allowing re-identification and re-evaluation of real options "in" system. New real options may be discovered with more information available.

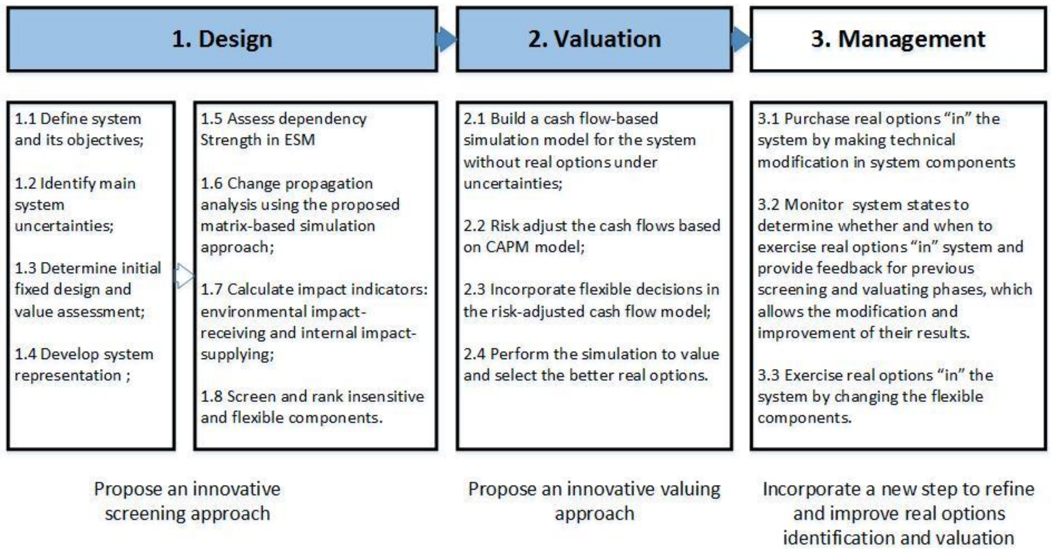



**Figure 6-1 Future extension of current research work**

Another research direction is to implement the proposed framework on practical systems. Although the UAV case study indicates that the proposed methodology works in a satisfying manner, it is better to have it implemented and validated by real complex engineering systems.

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# Appendix A

$$l_{2,1} = 1 - (1 - l_{2,1})(1 - l_{3,1} \times l_{2,3})\{1 - l_{4,1}[1 - (1 - l_{3,4} \times l_{2,3})(1 - l_{2,4})]\}$$

$$l_{3,1} = 1 - (1 - l_{3,1})(1 - l_{4,1} \times l_{3,4})$$

$$l_{4,1} = l_{4,1}$$

# Publications

**Journal papers:**

*1.* Y. Jiang and K.L. Poh. Identification of Flexible Design Opportunity in Complex System. Submitted to *IEEE Transactions on Engineering Management.*

*2.* Y. Jiang and K.L. Poh. A Matrix-Based Simulation Approach for Change Propagation Analysis. Submitted to *IEEE Transactions on Engineering Management.*

**Conference proceedings:**

1. Y. Jiang and K.L. Poh. Capacity Planning and Flexible System Design: A Real Options Analysis. In *Proceedings of the 5th Asia-Pacific Conference on Systems Engineering (APCOSE 2011)*, Seoul, Korea. October 19-21, 2011.