FLEXIBLE ENGINEERING SYSTEM DESIGN WITH MULTIPLE EXOGENOUS UNCERTAINTIES AND CHANGE PROPAGATION

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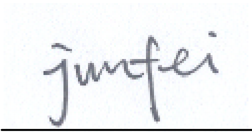
Declaration

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 the thesis.

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



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Summary

Complex engineering systems, such as transportation systems, often require a significant amount of capital investment and are often built for long-term use. In addition, these systems operate in changing environments, which can significantly impact system performance. Thus, how to successfully design a complex engineering system in the initial design phase and make it perform well under uncertainty has been a constant challenge faced by system engineers.

This research focuses on the problem of generating flexible design concept for engineering systems under uncertainty. Specifically, we are interested in identifying the elements in complex engineering systems that are suitable for designing flexibility. The methodology proposed in Chapter 3 aims to integrate Multi-attribute tradespace exploration (MATE) with set-based concept design to explore the design space more efficiently. It helps designers to generate and select a fixed design concept. Chapter 3 is a preliminary work and serves as a starting point to investigate the problem of design concept generation and selection. The methodology in Chapter 3 offers a relatively intuitive way to identify the design concepts without the consideration of uncertainty.

To improve the lifecycle performance of the complex engineering system, uncertainty and flexibility are further considered in the design concept generation process. A sensitivity-based method has been proposed in Chapter 4 to identify the flexible design opportunities. It builds upon existing

methodologies, which only consider the direct neighboring relationships and one major uncertainty in the generation of flexible design concepts. Although the sensitivity-based method is useful in identifying flexible design opportunities in some circumstance, it is proposed under some assumptions. For example, the degrees of dependency between the system elements are assumed to be the same. The sensitivity-based method is an intuitive and effective method to generate flexible design concept if these assumptions hold.

To select flexible design opportunities under a more realistic situation, a risk susceptibility method is proposed in Chapter 5. It removes the assumptions in the sensitivity-based method and focuses on identifying the system elements that are suitable for flexible design, by considering and predicting the potential effects of change propagation. The risk susceptibility method can help designers limit the number of flexible design concepts to consider and analyze in an early conceptual stage.

The sensitivity-based method and risk susceptibility method are demonstrated and evaluated in a High-Speed Rail (HSR) system. The flexible design opportunities in subsystem-level are firstly selected by the sensitivity-based method. The expected value of the total cost can be saved by enabling flexibility. In addition, the flexible design opportunities of the HSR system in parameter-level are selected by the risk susceptibility method. The result shows that the value of flexibility would increase as uncertainty increases. The result also confirms that the system element, identified using the proposed methodology, is a valuable choice for embedding flexibility.

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List of Abbreviations

ABS	Automatic block signal
ACS	Automatic cab signaling
BBN	Bayesian belief network
BLS	Blue line switch
BPM	Bayesian probabilistic model
BRT	Bus rapid transit
CPA	Change propagation analysis
CPI	Change propagation index
CPM	Change prediction method
CPT	Conditional probability table
CTA	Chicago transit authority
CTC	Centralized traffic control
DCF	Discounted cash flow
DSM	Design system matrix
DTM	Design theories and methodologies
EOS	Economies of Scale
ES	Express service
ESM	Engineering system matrix
FDOs	Flexible design opportunities
GBM	Geometric Brownian motion
HSR	High-speed rail
MATE	Multi-attribute tradespace exploration

PFU	Pareto front union
PSBC	Pareto set-based concept
RI	Region of interest
SBC	Set-based concept
sDSM	Sensitivity design system matrix
TSC	Train speed control

Chapter 1 Introduction

1.1 Background

Engineering systems, such as transportation system, industrial infrastructure, and energy system, are becoming increasingly important in the modern society. Well-developed engineering systems enhance the functionality of a society, while poorly developed engineering systems may cause event disasters and have significant economic and societal impact due to the amount of capital and people involved. Thus, how to successfully develop a complex engineering system has been a constant challenge faced by system engineers.

The development of a complex engineering system can be divided into four major phases: initial design phase, building/implementation phase, operational/management phase and redesign phase. Among the four phases, the initial design phase plays a critical role in the whole lifecycle. The International Council on System Engineering estimated that 70%-90% of the development cost of a system is determined after only 5%-10% of the development time has been completed(Haskins et al., 2006). A wrong decision in the initial design phase can have serious impact on the entire process, and it is difficult to correct such decision in the later development process. Therefore, the more complex a system is, the more important a careful design decision is needed in the initial system design phase.

In a typical initial design phase, three stages occur sequentially: the conceptual design, the preliminary design followed by the detail design (Ertas and Jones 1993). In the conceptual design stage, a design concept, which is a parametric model, is generated. It is just a concept with imprecise descriptions. In the preliminary design stage, system configuration of the preferred design concept is defined in accordance with technical and economic requirements. In the final detail design stage, a design alternative, which is a specific design of the concept defined by a unique set of design variables, is generated. Fig 1.1 shows the design process in the initial design phase.

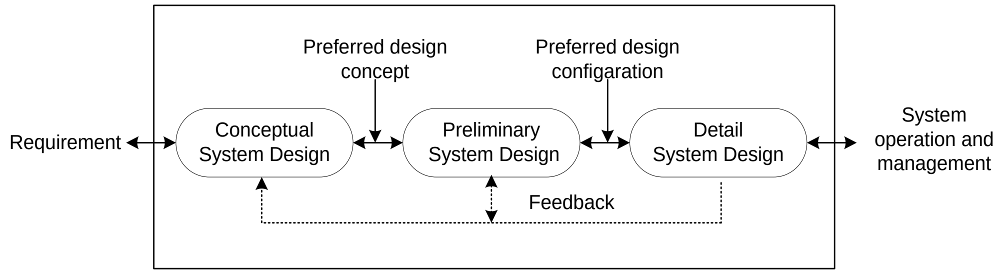


Fig 1.1 The initial design phase of engineering system

Many design theories and methodologies (DTM) have been proposed to support designers to make decisions in the initial design phase. Well-known examples of DTM are Axiomatic Design (Suh 1990), Robust design (Taguchi 1987), and TRIZ (Altshuller and Rodman 1999), etc. The existing DTMs address many problems in the initial design phase, such as how to generate and select design concepts, how to represent the interconnections of system elements, as well as how to manage the collaboration of the design process.

Although the existing DTMs are useful and successful in some circumstance, they still need to be improved in order to handle new challenges for today’s design activities. One of the most important challenges is how to design an engineering system, which can constantly provide profitability in a changing environment. Generally, engineering systems often involve huge initial investments and are built for long-term use. Within the long lifecycle of the engineering systems, significant uncertainties will occur from economic, environmental, political and technical innovation. Therefore, there is a need to develop methodologies to manage these uncertainties and reduce the risk in the operation and management phase.

1.2 Motivation

This thesis aims to address this new challenge in the engineering system design. We focus on design concept generation and selection problem in the initial design phase. Uncertainty and flexibility are further considered for the system design concepts, in order to make the complex systems adapt over time to provide good lifecycle performance. The research of the design concept generation and selection serves as a preliminary work of this thesis, which studies how to select competitive design concepts without uncertainty and limit resources in the detailed design phase. The main part of this thesis is how to embed flexibility into a system design concept. This section explains the motivations from two levels: the importance of design concept selection, and the need to recognize the uncertainty and flexibility in a system design concept.

1.2.1 Design Concept Generation and Selection

Because of the complexity of engineering systems, a large number of design alternatives may be generated in the detail design phase. Evaluating the full set of design alternatives may overwhelm system designers. In order to effectively and efficiently find optimal design solutions, system designers are required to simplify the design selection by decomposing the problem into a series of related decisions, such as design concept selection followed by design alternative selection. Eliminating the inferior concepts in the conceptual design phase can make the system designers focus their limited resources on the competitive concepts and efficiently specify optimal design alternatives in the detail design phase. Selecting an optimal design concept could reduce the impact of change in the latter design phases and significantly determine the success of the final design.

Although concept generation and selection plays an important role in the initial design phase, few optimization approaches have been developed for it. One possible explanation is that these conceptual design activities are challenging tasks for decision makers and system engineers. The main challenge is that only limited design information can be obtained in the early design phase (Crossley and Laananen 1996, Hazelrigg 1999, Rowell et al., 1999, Mattson and Messac 2002).

Recently, there have been increased efforts to develop approaches for concept generation and selection. One of the most powerful tools is the multi-objective optimization. In general, a set of optimal solutions, called Pareto optimal set, is obtained to model design concept in a multi-objective design problem. The most desirable design alternative within the Pareto optimal set will be finally selected. Representative examples are set-based concept (Avigad and Moshaiov 2009), Pareto Frontiers (Mattson and Messac 2002, Mattson et al., 2004) and parameterized Pareto set (Malak Jr and Paredis 2009, 2010).

Although the multi-objective optimization methods perform well in this research area, complex calculation process and domain technologies are needed to use such methods. Therefore, there is a need to fill a research gap: how to generate and select a system design concept in a simple and intuitive way. This thesis wishes to address this issue by providing a quantitative and qualitative framework for concept selection. The proposed framework explores the design space and selects a design concept based on the tradeoffs (i.e. decision-makers utility attributes and costs) of a set of design alternatives. The methodology hopes to select competitive concepts in the conceptual design phase and serves as a preliminary work for further considering flexibility in the design concept.

1.2.2 Uncertainty and Flexibility in Engineering System Design

The traditional methods for engineering system design often focus on optimizing the system's performance based on an assumption that the external environment is deterministic. Specifically, uncertainties are not recognized and considered in the engineering design. The traditional methods could lead to an optimal solution if the future is relatively stable. However, most of the engineering systems are set up for long-term use and the environment cannot keep in certain during the whole lifecycle in the real world. A set of rigid configurations of an engineering system is not easily modified to satisfy future needs, may lead to failure in the future.

Many examples of past events illustrate how uncertainty affects the engineering system. One of the famous examples is the communication satellite systems, which is described in de Weck et al., (2004). In the early

1990s, Low Earth Orbit constellations of communications satellites such as Iridium and Globalster were encouraged to develop. Both of these systems were commercial failures. The proximate cause of these failures is that designers and managers underestimated demand for land-based cell phones and overestimated demand for satellite service. Furthermore, the communication satellite systems were too inflexible to be downsized. This example illustrates the significant impact of uncertainty in the design of systems.

In the literature, there are many approaches to manage uncertainty. Flexibility is one of the useful approaches to pro-actively deal with uncertainty. Flexibility is related to the concept of real option "the right, but not the obligation to change a system in the face of uncertainty" (Trigeorgis 1996). Adding flexibility in the initial design phase can make the system change easily in light of changing circumstances (de Neufville and Scholtes 2011). Many applications, such as water resource systems (Wang 2005), offshore oil platforms (Kalligeros et al., 2006, Lin 2008), infrastructure systems (Zhao and Tseng 2003, Ajah and Herder 2005), transportation systems (Bowe and Lee 2004, McConnell and Sussman 2008), etc., have been shown that system design with flexibility can increase the overall performance (e.g. economic and non-economic) ranging between 10%-30%, compared to inflexible design.

Currently, most flexible design applications focus on valuating flexibility using financial formulas (Zhao and Tseng 2003, Ajah and Herder 2005, Wang 2005). The flexibility valuation methods assume that the information about where to embed the flexibility is available a priori (de

Neufville et al., 2006). However, identifying where to embed flexibility from a large number of system components is not an easy task because of the various system components and the linked interactions. Billions of possible flexible strategies can be generated in the analysis process. It is computationally expensive to fully compare all the flexible strategies. Therefore, there is a need to develop a methodology, which identifies the suitable elements in a system to add flexibility.

Based on the literature review, it has been found that most of the methods for identifying flexible design opportunities deal with individual uncertainty (Kalligeros 2006, Suh et al., 2007). In addition, only the direct influence relationships, which are simply transmitted to neighboring components, are considered (Jarratt et al., 2011). However, in the real world, multiple exogenous uncertainties may occur simultaneously. In addition, a simple change of one system element may trigger a change of other system elements, which may not directly connect with it. This simple change may finally propagate throughout the whole system and cause a significant change propagation impact. To this end, we aim to develop a straightforward and generic methodology to identify the system elements, which are suitable for designing flexibility in a system design concept. Hopefully, extend the existing works by considering multiple exogenous uncertainties and change propagation effect, with the goal of improving system performance.

1.3 Research Scope and Objectives

Motivated by the needs which are discussed above, this thesis is designed to address three research problems. The first research problem is how to generate and select the design concepts of a complex engineering system in a simple and intuitive way. The second research problem is the part of this thesis. It focuses on how to identify the elements in a system that might most advantageously be considered for flexibility, considering multiple exogenous uncertainties and complex change propagation effect. The third research problem is how to evaluate the proposed methodologies in a real application by comparing different design strategies with varying degree of uncertainty.

The thesis aims to achieve the following objectives:

- *To develop a simple and intuitive concept modeling and selection framework for complex engineering systems.* In order to achieve this objective, a Pareto Set-based Concept (PSBC) framework is proposed. It represents the design concepts by a set of reprehensive design alternatives in a Utility-Cost tradeoff space.
- *To propose a novel method to identify the system elements for designing flexibility with multiple exogenous uncertainties.* The proposed method, called sensitivity-based method, identifies flexible design opportunities based on the sensitivity of each system element. The sensitivity shows how much the system elements are influenced by the exogenous uncertainties. In order to find the entire influence paths from exogenous uncertainties to system elements, an exogenous factor searching algorithm and a flexible opportunity selection algorithm is developed.
- *To manage the change propagation in the flexible concept generation process.* In order to achieve this objective, a risk prediction method,

which predicts the risk of change propagation from both exogenous uncertainties and flexible options, is proposed.

- *To evaluate the effectiveness of the proposed methods.* In order to achieve this goal, we apply the proposed methods into a representative engineering system—High-Speed Rail (HSR) system. Flexible design opportunities in subsystem-level and parameter level are analyzed.

1.4 Contributions of the Thesis

The main contributions of this research can be categorized into three parts. The first part relates to the methodology for design concept generation and selection. A concept selection framework, called Pareto Set-based Concept (PSBC) method, is proposed for complex engineering system design. The PSBC framework evaluates design concepts on the utility and cost basis by incorporating Multi-Attributes Tradespace Exploration (MATE). Representative design alternatives are selected to model the performance of a design concept. Compared to the multi-objective optimization (Avigad and Moshaiov 2010, Zitzler et al., 2010), the PSBC framework could offer a more intuitive and efficient way for system designers to understand the trade-off of each design concept. In addition, it models the system concept by a subset of design alternatives in Pareto frontier rather than exploring the full set of design alternatives, thus save computational resources. By using PSBC framework, the competitive design concept could be efficiently selected in the early design phase. This might help decision makers to limit efforts in the detailed analysis process. A numerical example of transportation system has been constructed. It reveals that the optimal concept for decision makers highly depends on the selection criteria as well as the risk attitude of the decision makers. This finding is significant since it provides important criteria for decision makers to select design concepts in the initial design phase**.**

The second part relates to the methodology for generating flexible design concept. Different from the first part, uncertainty and flexibility are considered in the concept generation process. A sensitivity-based method is proposed to identify the elements in a system that might most advantageously to be considered for flexibility. The sensitivity is defined as whether the changes of exogenous factors can directly or indirectly trigger the changes of system elements. The quantitative measurement, which counts the number of exogenous factors for each system element, is also developed. The sensitivity-based method has provided valuable insight on how to identify flexible design opportunities when considering the multiple exogenous uncertainties. This is a significant improvement since the proposed method might serve as a realistic and holistic model. Compared to the existing methods, the sensitivity-based method provides a clear mechanism to understand complex interdependencies, which are not only within the system boundary but also outside it. This may help designers to consider both direct and indirect influence relationships in the design process. In this thesis, the sensitivity-based method is evaluated in a High-Speed Railway (HSR) system. The results show that the flexible strategy has 13.6% improvement (i.e. saving the expect lifecycle cost) over fixed strategy. This provides clear evidence that embedding flexibility in the selected elements which are recommended by the sensitivity-based method could improve the anticipate performance of the system.

The third part also relates to the methodology for generating flexible design concept. Departs from the part two, a risk prediction methodology is proposed to generate flexible system concepts by considering the change propagation effects. The Bayesian network is incorporated in the analysis process, in order to calculate a probability of change from both direct and indirect influence relationships. The proposed methodology selects and ranks a set of system elements by predicting and analyzing the risk of change propagation. The ranking information of system elements can help to limit the number of flexible design concepts to consider and analyze at an early conceptual stage, in contrast to other concept generation methods available in the literature. Furthermore, the ranking information provides clear guidance to designers and decision-makers, especially when they have limited analytical resources available. Considering the risk of change propagation in the initial design phase could provide a new research avenue for exploring flexible design opportunity. In this thesis, the risk prediction method is evaluated in a railway signal system. The results show that the value of flexibility would increase as uncertainty increases. In addition, the flexible design, which is generated by risk prediction method, has the lowest expected total cost in all scenarios with a high degree of uncertainty. This case study may not only provide the guidelines for system designers to respond to multiple exogenous uncertainties, but also prove that the risk prediction method is superior to the sensitivity-based method by further considering the effect of change propagation.

1.5 Organization of the Thesis

The remainder of this thesis is organized as follows:

- Chapter 2 provides a survey of flexible design theories and methodologies. The survey introduces the basic concept underlying this thesis. It reviews and summarizes the existing work. The research gaps are discussed in detail.
- Chapter 3 focuses on design concept generation and selection process without considering uncertainty. A PSBC framework is proposed to generate design concept in a simple and intuitive way. The procedures for modeling design concept by a large number of design alternatives in Pareto frontier, as well as mapping design alternatives with multi-objectives into a Utility-Cost tradeoff space are illustrated. The methodology proposed here helps designers to generate and select a standard design concept and serves as a starting point. A numerical study on transportation design problem is used to demonstrate the key procedures of the framework.
- Chapter 4 generates a design concept by explicit consideration of uncertainty and flexibility. The methodology proposed here aims to make the system adapt over time and improve the lifecycle performance of the system. A sensitivity-based method is proposed to identify the elements in a complex engineering system that are most worthy to be considered for flexibility under multiple exogenous uncertainties. The concept of sensitivity and the quantitative measurement of sensitivity in this thesis are first defined. The procedure of this method is explained.

- Chapter 5 also focuses on how to generate the flexible design concepts for the complex engineering systems. A risk prediction method, which extends the sensitivity-based method by taking into account the change propagation effect in the flexible concept generation process, is proposed. The reasons of considering the complex change propagation effect in the flexible design concept generation process are first discussed. Also, the procedure of how to predict the risk of change propagation is illustrated.
- Chapter 6 applies the sensitivity-based method to HSR system. The characteristic of HSR system is discussed. The exogenous uncertainties and subsystem-level design variables for HSR system are analyzed. Flexible design strategy is compared with an inflexible design strategy to evaluate the proposed method. One-way sensitivity analysis of uncertainty assumptions is conducted and analyzed.
- Chapter 7 applies the risk prediction method to the railway signal system. The characteristic and operation process of the railway signal system is introduced. The exogenous uncertainties, as well as the parameter-level design variables for the railway signal system are analyzed. The flexible design strategy, which is generated by the risk prediction method, is not only compared with an inflexible design strategy, but also compared with a flexible design strategy, which is generated by sensitivity-based method.
- Chapter 8 draws a conclusion of this thesis as well as some future challenges.

Fig 1.2 shows the main content of each chapter and the relationships among different chapters.

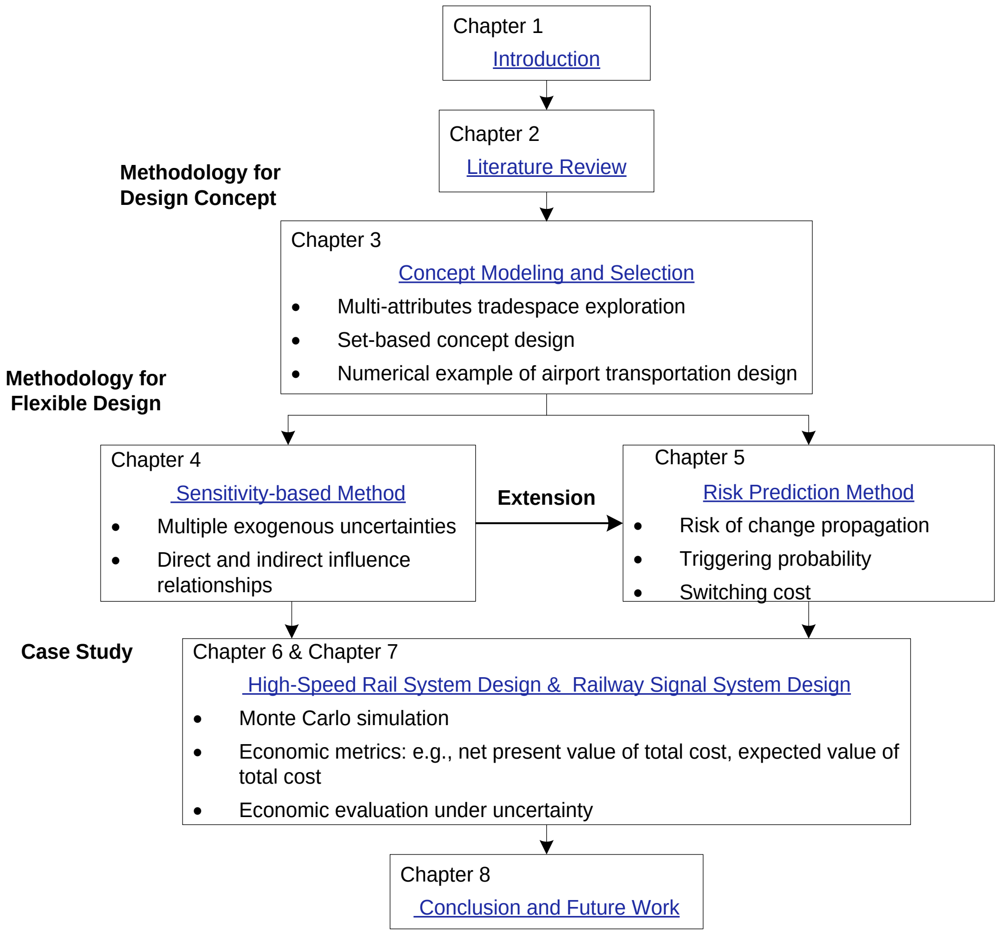


Fig 1.2 Structure of this thesis

Chapter 2 Literature Review

2.1 Introduction

This chapter serves as a foundation of this thesis. The goal is to provide an up-to-date review of existing works in engineering system design and show the research gaps in detail. The existing works reviewed in this chapter are drawn from multiple domains: system conceptual design, uncertainty and flexibility, flexible system design and change propagation management. The remainder of this review is organized as follows. Section 2.2 discusses the major existing works in system concept generation and selection. Section 2.3 illustrates the uncertainty in engineering system and various strategies to manage uncertainty. Section 2.4 provides a comparison of current methodologies for generating and selecting flexible design concept. Section 2.5 reviews the methodologies for predicting risk of change propagation in engineering design perspective. Section 2.6 summarizes this chapter.

2.2 System Conceptual Design

Design concepts are difficult to represent and generate, since they are just abstract ideas with imprecise descriptions. Traditionally, the concept can be represented verbally (Borgida and Brachman 2003), or by a parametric model (Al-Salka et al., 1998). The Theory of Inventive Problem Solving (TRIZ) is one of the system approaches for generating innovative solutions. It was developed by Altshuller et al., in 1973. A large number of patents are analyzed in order to find a set of fundamental design principles (Altshuller and Rodman 1999). Forty inventive principles are suggested to develop an efficient solution (Altshuller et al., 1997). The primary focus of this method is more on generating innovative concepts. In addition, it has great strength in resolving technique contradictions. TRIZ has been widely used in a variety of industries and services (Shirwaiker and Okudan 2008).

Another well-known method for system concept generation is Axiomatic Design. It is based on application of two axioms: independence axiom and information axiom, to systematically solve a give problem. Specifically, independence axiom states that the functional requirements of the problem should be independent of each other, and information axiom states that the better solution is the one with minimum information content (Suh 1990). Axiomatic Design breaks the main problem into different domains and analyzes effectiveness of the solution in terms of satisfying the two axioms. The concept generation process is to map customer attributes to functional requirements, and then determine design parameters and process variables. Different from TRIZ, Axiomatic Design concentrates more on problem definition.

The systematic approach to engineering design developed by Pahl and Beitz (1996) is also a popular method that is used in both industry and academic. This method is a systematic process guiding designers to select the solution. It divides the design process into a number of phases: clarification of task, conceptual design, embodiment design and detail design. The advantage of this method is that it focuses on the entire design process from system planning to detail design, which can provide a clear guide to designers.

Set-based concept (SBC) approach deviates from the traditional description. It is firstly proposed by Ward (1989) and then successfully applied in industry (Liker et al., 1996, Sobek et al., 1999). From the perspective of SBC approach, a concept should be viewed as a category of design alternatives. In contrast to the traditional approaches, a concept is perceived to have a one-to-many relation as in the SBC case. Currently, the SBC approach is further complicated in the multi-objective setting. Each of the design alternatives in the SBC is mapped to an objective space and assumed to be a point in the objective space, in order to represent its performance. The concept’s performance can be evaluated based on a set of design alternatives, which is associated to the particular concept.

Recent researches related to SBC approach focus on two topics. The first one is how to select a set of design alternatives to effectively represent the performance of a concept. Mattson and Messac (2003) introduced the s-Pareto frontier to classify concept dominance. Specific design alternatives were selected as s-Pareto optimal when no other alternatives exhibit improvement in all design objectives. The normal constraint method was used to effectively and efficiently find such s-Pareto front. Mattson and Messac (2005) further discussed the visualization problem for s-Pareto front. Several representative works are inspired by the s-Pareto methods, such as the smart Pareto filter (Mattson et al., 2004). In addition, the problem of indeterminacy of the SBC has been pointed out by Malak Jr et al., (2009). The parameterized Pareto set is proposed in order to avoid indeterminacy in the concept selection process. The effects of indeterminacy and the parameterized Pareto sets are fully explained in (Malak Jr and Paredis 2009, 2010). Based on the parameterized

Pareto set, a design concept can be generated using the information about prior design alternatives. It overcomes the limited reusability problem for traditional Pareto frontiers. The second research topic is how to choose the selection criteria in the conceptual design phase. The traditional approaches in multi-objective problem are usually based on the optimality (e.g. Mattson and Messac 2005). According to Avigad and Moshaiov (2009, 2010), the selection criteria can be extended to two dimensions: both optimality and variability of concepts.

The SBC approach in multi-objective setting improves the concept generation and selection in engineering design. However, the calculation process may be overwhelming, since a large number of design variables, parameter, and design constrains need to be considered. Therefore, there is a need to develop a systematic and efficient technique that facilitates the design concept generation and selection. This thesis aims to address this problem by mapping multiple objectives into Utility-Cost dimensions. The goal is to provide an intuitive representation of system concepts to better support concept selection in the conceptual design phase. (Details are discussed in Chapter 3).

2.3 Uncertainty and Flexibility

2.3.1 Uncertainty and Uncertainty Management

Here, uncertainty reflects the factors, which affect the future performance of an engineering system, such as travel demand and commodity prices. According to de Weck et al., (2007), uncertainties can be mainly classified into two groups based on the sources:

- *Endogenous uncertainty:* is the uncertainty, which arises primarily within system boundary, such as technical risk. Understanding this type of uncertainty requires domain knowledge of the technical systems.
- *Exogenous uncertainty:* is outside of the direct control of decision makers, as it arises from the environment in which the system is operated. Examples of exogenous uncertainty include customer demand, different climate or weather conditions.

As demonstrated by numerous case studies in de Weck et al., (2007), uncertainty can significantly impact the success or failure of engineering systems. Research issues for uncertainty management in engineering system design are discussed by de Neufville et al., (2004). A two-way methodology for managing uncertainty: time scales and modes of response are developed in that paper. As for the time scales, the decision makers can manage uncertainty from operational level, tactical level and strategic level. These three types of management deal with uncertainty from short term to long term. As for the modes of response, one can enable a system to respond to uncertainty passively or actively. Robust design is an example of the passive approach to managing uncertainty. It allows a system to satisfy a fixed set of requirements, despite changes in the environment. Different from passive approach, active approach is to design flexibility into systems. Flexible design may give the system an ability to change easily as uncertainty unfolds in the future.

Fricke and Schulz (2005) proposed that designing changeability in a system can deal with uncertainties from the exogenous and endogenous environment. Flexibility, agility, robustness and adaptability are four key aspects of changeability (They are illustrated in Fig 2.1). Robustness characterizes a system's ability to be insensitive towards changing environments. It handles uncertainty (change) without changing system architectures. Flexibility characterizes a system's ability to be changed easily. It handles uncertainty (change) by changing system architectures or designs. Agility characterizes a system's ability to be changed rapidly. And adaptability characterizes a system's ability to adapt itself towards changing environments.

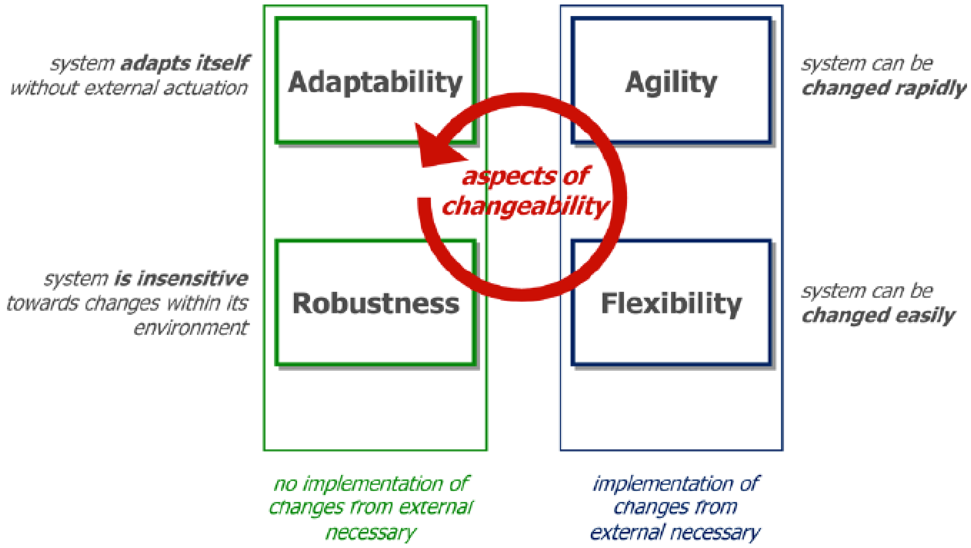


Fig 2.1 The four aspects of changeability

(It is originally from Fricke and Schulz (2005))

Ross et al., (2008) further defined and classified different parts of the core concept of "changeability" from three aspects: change agents, change effects, and change mechanisms. First, different parts of changeability may have different change agents. Change agent here is defined as the force instigator for the change to occur. If the change agent is external to the system, flexible design is considered. On the other hand, if the change agent is internal to the system, adaptable design may be more suitable. Second, the change effect of robustness is quite different from other parts of changeability. The change effect here is defined as the difference in the states before and after a change has taken place. No change occurs in robust design, despite changes in the environment or within the system. In contrast, other parts of changeability deliver value through altering the system to meet new environments.

Based on the literature, we can summarize that robust design and flexible design are two important ways to deal with uncertainties. Flexibility in engineering design enables a system to change easily in the face of uncertainty (de Neufville and Scholtes 2011). A flexible design represents a design where the system has the ability to adapt flexibly when uncertainties occur. It is different conceptually from a robust design, which makes a system's function more consistent despite variations in the environment, manufacturing, deterioration, and customer use patterns (Jugulum and Frey 2007). It should be noted that we focus on flexible design in this thesis. In addition, we will limit our effort to analyze exogenous uncertainty in this thesis, since the change agent for flexible design is external to the system.

2.3.2 Flexibility and Real Options

Flexibility is a multi-disciplinary concept that means different things if the context change. Saleh et al., (2009) analyzed flexibility in the context of decision theory, real options and management, manufacturing system and engineering design. In this thesis, we only summarize the definition in the area of engineering system design.

In the engineering system design literature, flexibility is associated to the concept of a real option, which provides the “right, but not the obligation to change a system in the face of uncertainty” (Trigeorgis 1996). It enables a system to change easily in the face of uncertainty (de Neufville and Scholtes 2011). The flexible design is different conceptually from a robust design, which makes a system’s function more consistent despite variations in the environment, manufacturing, deterioration, and customer use patterns (Jugulum and Frey 2007).

One example of flexible design in real estate is the ability to expand a building vertically. The designer enables flexibility/real option in a building by stronger structure initially. The HCSC building in Chicago is a real case to exploit this flexible strategy. It was built to be a small capacity building and add additional stories only if there was a need (Guma et al., 2009). This flexible strategy could reduce the risk of loss since less initial investment was required. Also, it could capture more profits when favorable market conditions occur, by building more office. The owner company exercised the flexibility and expanded the capacity of HCSC building a few years ago.

Flexibility has been shown to improve the lifecycle performance by 10%-30% in comparison to a standard design and evaluation approaches (de Neufville and Scholtes 2011). Two ways of embedding flexibility in engineering system design are proposed in the literature -- *real options “on” project*, and *real options “in” project* (Wang 2005). Real options “on” project treat the whole system as a "black box". It focuses on managerial flexibility, providing decision-makers the options to make strategic decisions at a later stage. Examples of this kind of managerial flexibility are “abandon or defer investment", "expand a system's capacity" and "switch inputs/outputs". Real options "in" project refer to the flexibility within the system, which focuses on how the system elements can be changed adaptively to a changing environment (de Neufville et al., 2006). A flexible design concept can also be characterized by a *strategy* (or type) and *enabler* in design (or mechanism) (Mikaelian et al., 2011, 2012). A *type* is similar to the real option "on" project (e.g. expand, switch). A *mechanism* is an action, decision, or entity enabling the real option.

Currently, there are two main research topics in the area of flexible design in engineering system: 1) how to identify design opportunities to embed flexibility; and 2) how to build an appraisal mechanism to valuate flexibility. Most research efforts focus on constructing an appraisal mechanism to evaluate flexibility. The aim is to quantify the benefits of flexibility and further compare it to the additional costs required to enable flexibility. The work done in the Real Option Analysis (ROA) community enables a quantitative evaluation of flexibility in engineering design (Trigeorgis 1996). Many real case studies have shown that flexibility improves expected lifecycle performance. However, most studies are based on the assumption that the flexible concepts are available a priori. In practice, decision-makers may not be clear where to focus the design effort for flexibility, since a large number of design variables, complex interdependencies and various uncertainty scenarios have to be considered. Nowadays, many researchers realize that where/how to generate flexibility for engineering system is an important task, with the goal of achieving realistic design methodologies. Therefore, it becomes an attractive research topic in engineering design.

Motivated by this, we focus on the research problem of generating flexible design concepts for complex engineering systems. Specifically, we select the elements in systems, which are most worthy for designing flexibility, and these selected elements are called as flexible design opportunities (FDOs) in this thesis. We aim to provide a practical design methodology for identifying FDOs. Fig 2.2 shows a big picture of the research area in engineering system design and emphasizes the specific research topic in this thesis.

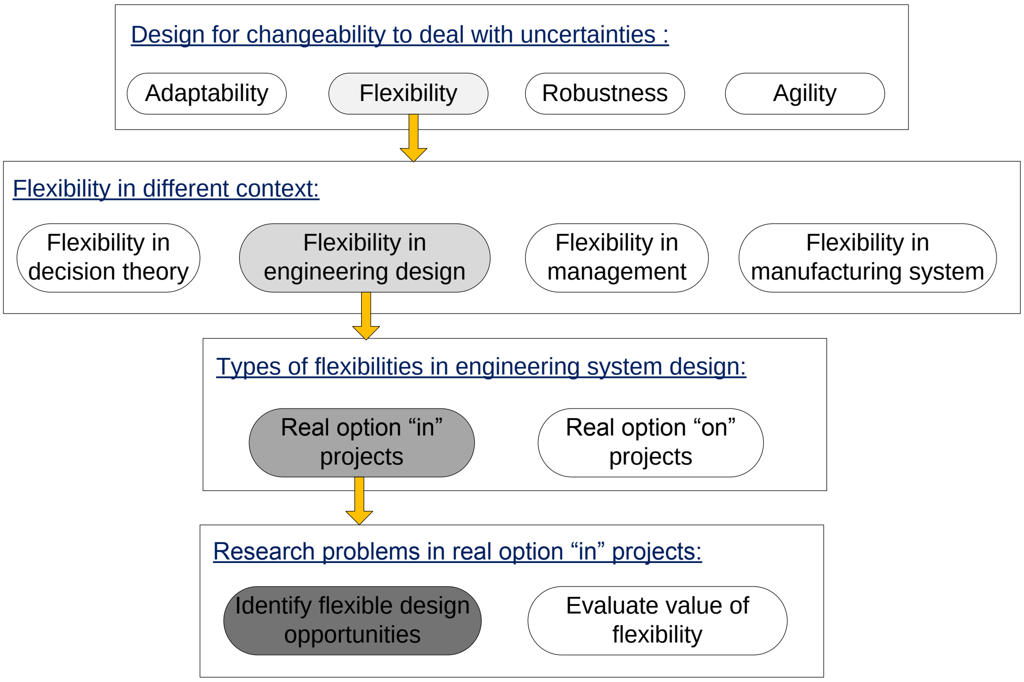


Fig 2.2 Specific research problems in the area of flexible engineering system design

2.4 Flexible System Design

This section provides an overview of existing works in flexible system design. Section 2.4.1 discusses the methodologies for identifying FDOs "in" engineering system. The goal is to point out research opportunities in this area. Section 2.4.2 summarizes the methodologies for flexibility valuation, in order to select a suitable evaluation method that can apply to case studies in this thesis.

2.4.1 Methodology for Flexible Design Concept Generation

Recently, several methods have been developed to address the problem of where to embed flexibility in the design process. These methods can be divided into two major categories: the screening methods and the Design System Matrix (DSM) -based methods. The screening methods are widely used to explore the design space to find valuable system configurations by building mathematical models. Wang (2005) proposed an optimization screening method, which screened out different designs using various combinations of design variables. This screening method is used to design a river dam for hydroelectric power production in China. The representative exogenous scenarios are prior information, which is assumed to be identified before modeling. Each exogenous scenario could find an optimal design configuration. The design variables that are altered from one optimal design to another design show good opportunities to embed flexibility. This method provides an efficient way of exploring the design space. However, it is difficult to select a set of representative scenarios of exogenous factors before modeling. In addition, computational resource is another problem when finding the optimal solution for large-scale engineering systems. In order to save the computational resource, screening methods are extended by building different levels of complexity model, or improving the searching algorithm (Lin 2008, Wilds 2008, Yang 2009, Cardin 2011). Although screening methods can quantitatively measure each design combination, it is difficult to represent system using a mathematical model when large numbers of design variables and highly interactive and complex relationships are involved.

Another group of methods for identifying FDOs is the DSM-based methods. DSM is basically a square matrix with identical row and column heading, which offers network modeling tools to represent the elements of a system and their interactions (Browning 2001, Eppinger and Browning 2012). Earlier, the DSM method focused on analyzing design activities and tasks (Steward 1981, Park and Cutkosky 1999). Later, it was extended to analyze technical artifacts (Pimmler and Eppinger 1994), organizations (Eppinger 1997), as well as parameters (Smith and Eppinger 1997). A detailed discussion of the DSM and its extensions are summarized in Bartolomei et al., (2007) and Eppinger and Browning (2012). Here, we focus on the methodologies, which are related to DSM in the area of flexible engineering system design.

Change Propagation Analysis (CPA) method is one of the representative methods in the DSM community. CPA uses a DSM matrix to represent the system components, the interconnections and information flows. The change propagation index was proposed by Suh et al., (2007) to measure the difference between the amount of change "in" a component and the amount of change "out" to others. The change propagation index can be calculated by Eq. (2.1):

$$CPI_i = \sum_{j=1}^{n} \Delta E_{j,i} - \sum_{k=1}^{n} \Delta E_{i,k} = \Delta E_{out,i} - \Delta E_{in,i} \qquad (2.1)$$

According to Suh et al., (2007), the components which propagate more changes to other components than they received are prime candidates for incorporating flexibility. The more these components are changed, the more changes are propagated through the whole system, thus the higher the total switching cost. And adding flexibility to these components could provide "buffer" to absorb some change as well as generate change.

Another DSM-based method is the sensitivity Design Structure Matrix (sDSM). It was used to develop platform design process (Kalligeros 2006). The sDSM method looked for the design variables, which are insensitive to the changes of design variables and functional requirements. The Invariant Design Rules (IDR) algorithm was presented accordingly to identify the potential platform components. Once the platform components were identified, designers can limit their effort to further evaluate these components. The sDSM is suitable when the direct relationships are easily identified in the early design phase.

The CPA method and sDSM method only consider the technical environment of system to explore the source of uncertainties. In order to overcome this drawback, the Engineering System Matrix (ESM) was introduced by Bartolomei (2007) to represent the system and its social-technical intricacies. The ESM was extended from the CPA method and the sDSM method by not only considering the uncertainties from the technical environment, but also taking into account the uncertainties from the human and social environment.

Although existing methodologies are applicable and effective in different circumstances, several challenging and important issues need to be considered. First, flexible concept generation methodologies aim to improve the concept generation phase, with the goal of systematically creating better design concepts. However, a large number of feasible concepts are generated and the decision-makers need to analyze and evaluate all the concepts before making decision. Second, the methodologies based on DSM method can provide a clear view of design variables and their complex interdependencies to identify FDOs. However, they have been mostly used for product platform design, and it is unclear how to use them for engineering systems that are typically more complex. In addition, they do not address the issue of considering complex change propagation phenomena. For example, in the CPA method, the change propagation index of a particular element is measured by comparing the direct change "in" the element and the direct change "out" the element. Another example is sDSM, by which the insensitive platform component is selected only when there are no direct relationships from functional requirements and other design variables to it. However, in the real world, a simple change to one part will propagate though a system and result in changes to a series of others, due to the highly connected relationships within the system. Only considering the direct relationship may lead to suboptimal solutions in the real world analysis (We will give a detailed literature review for change propagation in section 2.5). Third, the methodologies based on DSM methods for identifying FDOs only consider one main uncertainty source. Further research is needed to understand how to identify FDOs when multiple uncertainties are considered simultaneously.

This thesis addresses some of these issues by suggesting a novel methodology, which extends and merges recent development techniques from the fields of engineering design, change propagation management, and Bayesian network analysis.

2.4.2 Methodology for Flexibility Valuation

Various valuation techniques have been developed to valuate flexibility (real option). In this subsection, we discuss several representative methods based on a survey provided by Cardin and de Neufville (2008). Assumptions of each technique as well as the advantages and limitations for applying them are analyzed.

The Black-Scholes equation is the most famous option valuation method. It was proposed by Black and Scholes (1973), and became a foundation for valuation techniques. This closed form solution requires little computation time or few resources. However, it is constrained in the way that the real option problem should satisfy all the assumptions stated in the model, such as the uncertainty of the underlying assets should follow Geometric Brownian Motion (GBM) process. Thus, the application domain of Black-Scholes formula becomes very limited.

Decision tree analysis is a discrete representation for valuating flexibility. It represents possible scenarios of uncertainty and associated decisions with a tree structure. In this method, the value of flexibility is found by comparing the expected value of the decision path. Decision tree analysis can be used to model managerial flexibility in discrete time. However, it also has some limitations. Brandão et al., (2005) pointed out that decision tree analysis does not provide a correct valuation of flexibility, since it solved the valuation problem using same risk-adjusted discount rate of the original project without options. In addition, the decision tree formulation does not explicitly include the time axis or provide guidelines for accounting for the time value of money (Gustafsson and Salo 2004).

Binomial Lattice is another discrete method to represent stochastic differential equations. It was developed by Cox et al., (1979). There are two states: up and down, with some probabilities to represent the underlying asset. In order to reduce the number of possible paths, path independence is assumed. The binomial lattice is flexible since it can be combined with some efficient methods such as dynamic programming to value flexibility. In addition, it can clearly present the paths of project value across the time duration. As for the limitation, the binomial lattice requires good understanding of economic option theory. It is not a straightforward method for system designers. Furthermore, the path independence assumption may limit the application of this method.

Currently, de Neufville et al., (2006) proposed a valuation approach based on Monte Carlo simulation. This method involves three steps: 1) the standard discounted cash flow (DCF) analysis is performed. 2) A stochastic process is incorporated to simulate exogenous factors. Several stochastic scenarios are simulated and a distribution of possible outcomes is provided. 3) Flexibility is incorporated in the DCF analysis and a distribution of outcomes with flexibility is obtained. The difference between the outcome with flexibility and that without flexibility leads to an approximate measure of the value of flexibility. The advantage of this simulation method is that various design and management decision rules can be implemented. In addition, several sources of uncertainty can be treated simultaneously. Compared to other valuation techniques, this simulation method does not require deep knowledge of economic options theory. It is a transparent method for decision makers.

As a summary, each of the valuation methods provides valuable insight on flexibility analysis. Since the simulation method has significant advantages in modeling multiple uncertainties, it is selected to evaluate the proposed method in our case study. Different from other case studies, which evaluate system performance from a profit perspective, the performance in our case study evaluated from a cost perspective. Specifically, we emphasize on the expected value of the total costs. In this thesis, the value of flexibility is defined as “the difference between the expected value of the total cost of flexible design and that of the inflexible design”. The value of flexibility represents how much cost can be saved by means of flexible options. Conversely, $V_{flexibility}$ can be a negative value. This is because that additional cost is required to enable flexible options compared with inflexible design. If the flexible options are not exercised, the expected value of total costs for flexible design may larger than that of inflexible design. This means that the flexible option is not worthy to embed. In this thesis, the value of flexibility can be mathematically calculated by Eq. (2.2):

$$V_{flexibility} = E[TC]_{inflexible} - E[TC]_{flexible} \tag{2.2}$$

2.5 Change Propagation Management

Within complex engineering systems, system elements are closely linked with each other. A simple change of one system element may not only trigger the change of neighboring system elements, but also propagate the impact to other non-adjacent system elements. This change propagation phenomenon may cause significant impact to the whole system. Currently, many researchers make their efforts to effectively manage change propagation in engineering systems. Jarratt et al., (2011) provided a comprehensive review of change propagation management and summarized the existing work from different perspectives, such as the nature of the change propagation process, the tools and methods to support decisions in change propagation process, the strategies to cope with change propagation effect.

In an attempt to better manage change propagation, many methodologies have been proposed to model the change propagation process and assess the effects of change propagation. Eckert et al., (2004) identified two types of change: the emergent changes and the initiated changes by analyzing Westland Helicopters. They suggested that successful change management needs to be informed of design information such as the source of change, interdependencies, types of propagation behavior, the state of tolerance margins on key parameters, and consequences of change on product quality, cost and time to market. This work has further led to the development of change prediction method (CPM) to identify the risk of change in Westland Helicopters.

Clarkson et al., (2004) described the change prediction method (CPM) using DSM representation. It extended the change analysis beyond direct dependencies. The likelihood of the occurrence of changes and the impact of subsequent changes are considered in the CPM method. These values are used to calculate a risk matrix, which shows the risk of change propagation from one component to another, taking into account direct and indirect paths. Fig 2.3 shows how to use DSM to predict risk of change propagation. It was summarized by Koh et al., (2012).

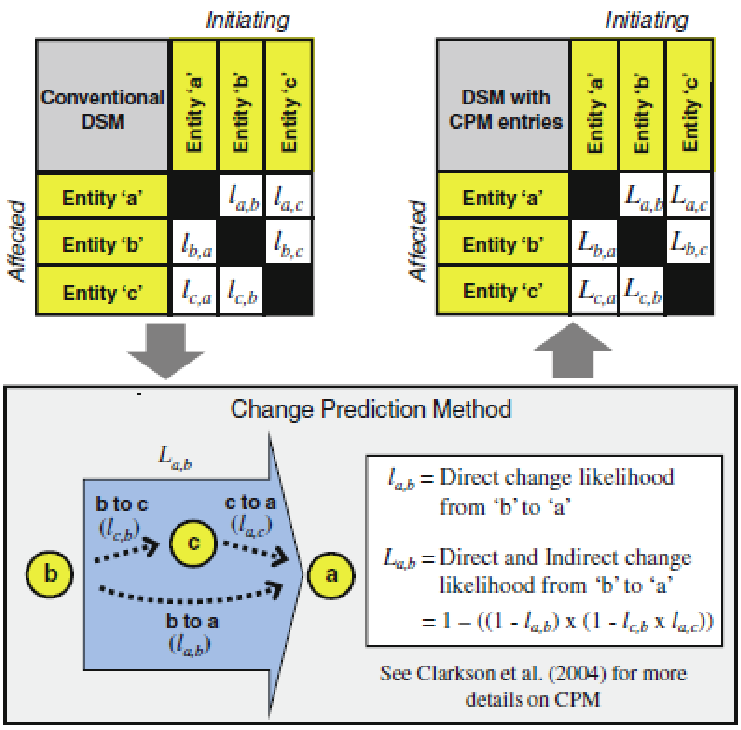


Fig 2.3 The change prediction method (CPM) using the design structure matrix (DSM)

Recently, the CPM approach has been used and applied to a number of engineering change management problems. Oh et al., (2007) used CPM to explore change absorbing architectures. Wynn et al., (2010) applied CPM to assist in identifying the value of change prediction. Keller et al., (2005) made efforts to the visualization technique for change propagation. In addition, Keller et al., (2009) applied CPM to support conceptual design. Multiple views on change propagation data were also visualized using the CPM tool. Giffin et al., (2009) analyzed a large data set to better understand the nature of change and change propagation.

To date, the CPM approach has been applied into different domain. However, most of the papers analyze interdependency and change propagation from a single domain—component domain (e.g. methods which are discussed above). Attempts to expand the analysis across different design domains have been suggested by some researchers. Tang et al., (2008) modeled how system elements, which are in the product domain, the process domain and the organization domain, can be affected through engineering change propagation. Pasqual and de Weck (2011) introduced a multilayer network model which integrates three coupled layers: product layer, change layer, and social layer. Koh et al., (2012) integrated the house of quality method and the CPM method to model the effects of potential change propagation. They focused on interdependencies in component domain, change option domain and requirement domain. The CPM approach and its extensions provide the information to allow changes that are easier to implement, as well as avoid changes that have more impacts to whole system in the redesign phase. However, most of the applications deal with individual change (uncertainty). In practice, often multiple changes (uncertainties) occur at the same time.

Beside the CPM approach and its extensions, other forms of change management techniques exist. Bayesian network is another representative technique to represent the causal relationships of architectural elements.

Moullec et al., (2012, 2013) used Bayesian network to generate system architecture. Tang et al., (2007) applied Bayesian Belief Networks (BBN) to build an architecture rational and element linkage model. This method captured the probabilistic causal relationships between design elements and decisions. Mirarab et al., (2007) and Zhou et al., (2008) extended BBN to predict change propagation phenomenon in software systems. The main advantage for using Bayesian network to model dependencies of system components is that it enables the designers to simulate multiple changes (uncertainties) at the same time. In addition, it allows designers to predict risk of change propagation from both direct and indirect perspectives.

The existing methodologies are mainly applied in the redesign phase. The objective is to avoid the undesired change propagation, when the engineers aim to change a complete product design to a future generation. However, not much work takes into account the potential effect of change propagation during the concept generation process in the initial design phase. In fact, embedding flexibility in design concepts makes the system more changeable. The engineering system can be changed by implementing the flexible option in its operational process to adapt new environment condition. If the change will trigger a significant cost to the whole system, this flexible option may not worthy to invest in the initial design phase. Therefore, there is a need to differentiate between the elements that are suitable for fixed design and the ones that are suitable for flexible design, by considering and predicting the potential effects of change propagation. de Weck et al., (2004) is one example to consider the change effect when generating flexible design concept for satellite communication system. The design variables: orbital altitude and minimum elevation angle are selected to be the candidates for designing flexibility, since changing these two design variables may not cause any changes in the hardware of the satellites in the future. This example provides a way to screen out a smaller number of candidate elements for flexibility. However, there is no efficient and general procedure to predict potential change propagation effect in the initial design phase and help designers identify suitable elements for flexibility. This paper aims to address this issue by adapting existing procedures in the flexible concept generation process, such as CPM by Clarkson et al., (2004) .

2.6 Summary

In this chapter, we have done a comprehensive survey from multiple domains: system conceptual design, uncertainty and flexibility, flexible system design and change propagation management. Several observations and research gaps have been drawn from the review. First, the system concept generation and selection play a significant role in the system design phase. Developing a systematic and efficient technique that facilitates the design concept generation of the complex engineering system becomes a valuable research area nowadays. Second, uncertainties can significantly influence the success or failure of engineering systems. Many case studies have been shown that flexibility provides an effective way to deal with uncertainty. Currently, one of the challenges for designing flexible option in engineering system is to clearly identify FDOs. Third, the existing methodologies for identifying FDOs can screen out valuable design strategies in some circumstance. However, how to realistically model system design with multiple exogenous uncertainties as well as change propagation are still limited. This literature review provides insights into the research area of flexible design theories and methodologies.

Chapter 3 Pareto Set-based Concept Modeling and Selection

3.1 Introduction

Currently, multi-objective optimization methodologies are widely used in generating design concept in the initial design phase (e.g. Mattson and Messac 2003, Avigad and Moshaiov 2009). Although these methods help the designers generate design concept, the calculation process may be overwhelming for analyzing a complex engineering system. This is because that a large number of design variables, parameters, and design constraints should be considered for the complex engineering system. Therefore, there is a need to develop a systematic and efficient technique that facilitates the design concept generation of the complex engineering system. The research work in Chapter 3 aims to fill this research gap. A framework, called Pareto set-based concept (PSBC) selection, is builds on the Set-based Concept (SBC) approach and the Multi-attribute Tradespace Exploration (MATE) method. It could efficiently explore the design space and select a design concept based on the tradeoffs (i.e. decision-makers utility attributes and costs) of a set of design alternatives. The performance of each design concept can be clearly represented and relatively easy to explain to a wide audience. Section 3.2 introduces the MATE method and explains the reasons for using the MATE method to map multiple objectives of the design concept. Section 3.3 presents the detailed procedure of the PSBC framework, which includes identification phase, concept and design alternative generation phase, concept modeling and selection phase. Section 3.4 conducts a numerical example to evaluate the PSBC framework. Section 3.5 provides a summary of this chapter.

3.2 Multi-Attribute Tradespace Exploration in Set-based Concept Design

Multi-attribute tradespace exploration (MATE) is a conceptual design methodology that applies decision theory to model and simulate design alternatives (Ross 2003, Ross et al., 2004). It is both a solution generating as well as a decision-making framework. Nowadays, MATE has been widely used in the area of the Aerospace system and Department of Defense in United States. The application domain involves space system architecting and design (Ross 2003), spiral design (Roberts 2003), value robustness (Ross 2006), system of system (Chattopadhyay 2009), survivability for conceptual design (Richards et al., 2009), and transportation system (Nickel 2010).

The procedures of the MATE method are provided in Ross (2003). We summarize the process in several phases. In the first phase, the stakeholder defines the attributes, which measure how well the objectives are met. In addition, single-attribute curves and preferences are elicited from decision makers. In order to arrive at an aggregate utility function, these single-attribute utility curves are aggregated using multi-attribute theory. Design variables are proposed according to the design attributes in the second phase, which is called the alternative generation phase. The particular design alternative is formed by a unique combination of the design variables. The set of all possible design alternatives constitutes the whole design space. The performance of the design alternatives is mapped to the utility-cost tradeoff space by the utility and cost function, which is assumed to be a point in the tradeoff space. The last phase is the evaluation phase. The Pareto-efficient alternatives are then considered in the further analysis.

The MATE method offers an easy and effective way to identify a large number of design alternatives by using computer technology. It evaluates design alternatives on the utility and cost basis. Comparing to the multi-objective setting, the two dimensions tradeoff space is more intuitive and efficient for the decision makers. This is because that the objective of a design concept (e.g. better fuel economy less and accelerate time for a vehicle design) could map to utility and cost for decision makers and the performance of each design concept can be represented in the tradeoff space. For example, it is difficult to compare different objectives such as safety and flexibility at the same time. However, it is possible to evaluate various objectives from the utility and cost perspective. More specially, the more safety or more flexibility, the more utilities are provided to decision makers. Under this circumstance, various design alternatives that focus on different objectives can be compared in the same tradeoff space. Obviously, the MATE method overcomes the limitations of the SBC design in the multi-objective setting as discussed previously. By using the MATE method to generate the full set of design alternatives and transform each of the design alternatives into performance in the utility-cost tradeoff space, the SBC approach may become more intuitive for decision makers.

3.3 The Proposed Framework

Based on the reasons discussed above, a Pareto Set-based concept framework is proposed in this section. This framework is built on MATE method and SBC approach. Section 3.3.1 gives an overview of this framework. Section 3.3.2 introduces the procedures of this framework.

3.3.1 Framework Overview

Fig 3.1 shows the Pareto set-based concept (PSBC) framework. This concept selection framework consists of four phases: identification, concept and alternative generation, concept modeling and concept selection.

In the identification phase, the objectives of an engineering system are defined and specified with attributes. The attributes and their associated utility curves are elicited in interviews by asking decision makers some questions. The decision maker also determines the design variables, which can be controlled. The major processes in this stage are similar to the identification phase in MATE method, which is fully explained in Ross (2003).

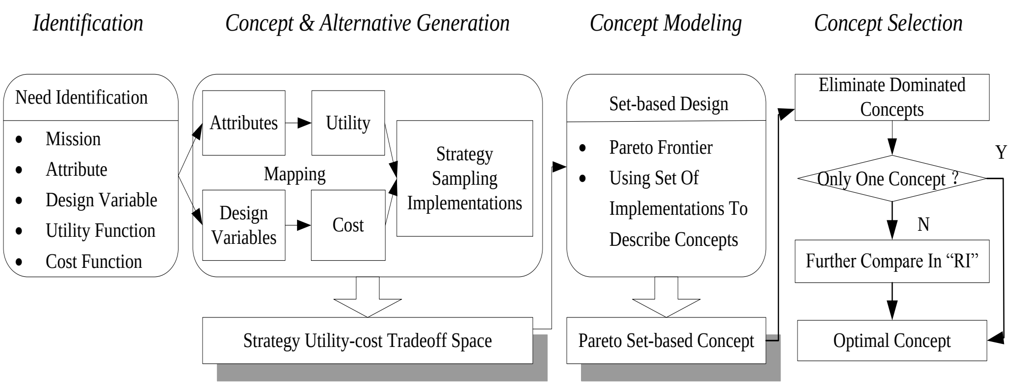


Fig 3.1 The Pareto set-based concept framework

In the second phase, the design concept and corresponding design alternatives are generated in the Utility-Cost tradeoff space. A design space in our definition is characterized by a set of design variables. By assigning different value to these variables, the design alternatives for a design space can be formed. When we consider multiple design spaces, these spaces could be characterized by different sets of design variables. Therefore, it is difficult to compare the design alternative from one design space with the one from another space, as they are different not only by design variables' value, but also by the dimension of these variables. Take vehicle design for example. The key design attributes of vehicle design are fuel economy, vehicle roominess, acceleration, reliability. Some design concepts may have better fuel economy, while others may have less accelerate time. Moreover, these design concepts are controlled by different design variables and are difficult to compare. The MATE method is used to overcome this limitation. Under PSBC selection framework, different design spaces are mapped to the Utility-Cost tradeoff space by using MATE. All the alternatives are presented in the same tradeoff space, no matter which design space they come from. Fig 3.2 shows the relationship between the design space and the Utility-Cost tradeoff space.

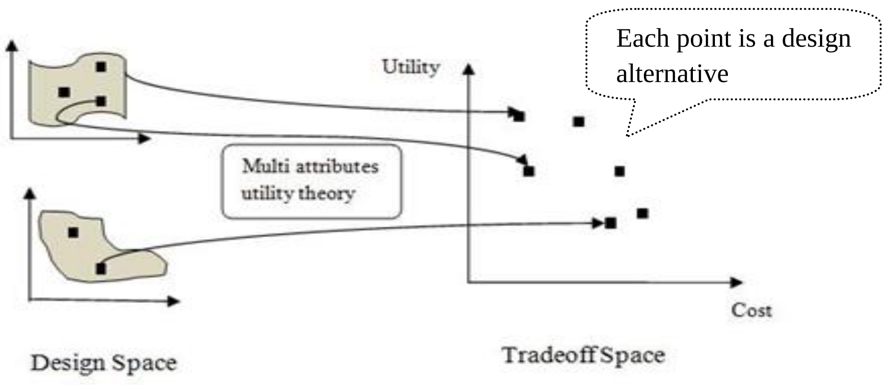


Fig 3.2 Mapping the design spaces to the Utility-Cost tradeoff space

Mathematically, the single attribute utility can be described as:

$$u_i = V_i\left(x_i^q\right) \tag{3.1}$$

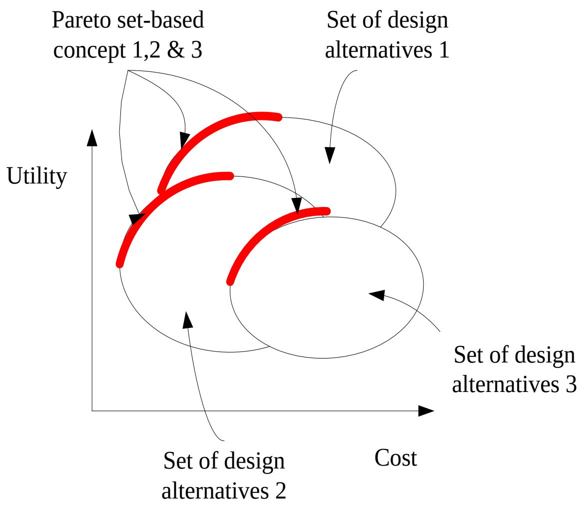
where u_i is the utility for i^{th} design attribute, x_i^q is the i^{th} design variable which is related to design concept q, $V_i(\cdot)$ is a single utility function for i^{th} design attribute, which is elicited from decision maker for mapping the design attribute to the tradeoff space. To map the design concept that has more than one attribute of interest, single attribute utility functions $V_i(\cdot)$ should to be integrated into a multi-attribute utility function $V(\cdot)$. In this framework, the weighted sum utility function is used. The main reason for using the weighted sum utility function is that the function is under an assumption: additive independence assumption. This assumption means that there are no cross-term benefits for the multiple attributes. Compared to other methods that are under restricted assumptions, the weighted sum utility function could be easily applied to a general situation. As for the weight in the function, it is set by the decision-maker to reflect the relative importance of the design attribute. The function is shown in Eq. (3.2):

$$U\left(x_1^q, x_2^q, \cdots, x_n^q\right) = \sum_{i=1}^{n} k_i\, V_i(x_i^q) \tag{3.2}$$

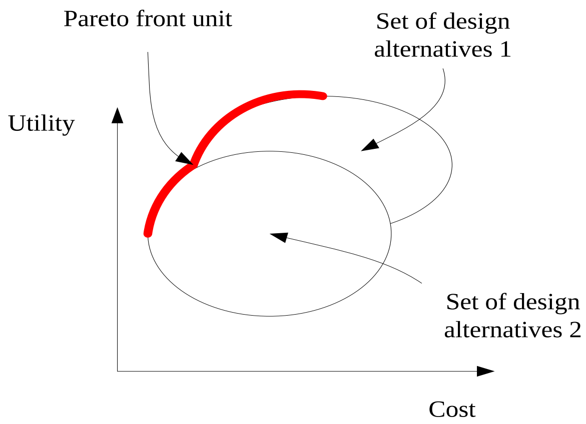
where $\sum_{\mathrm{i=1}}^{\mathrm{n}} k_i = 1$, k_i is a single-attribute weight constant, n is the total number of attributes.

At the end of this phase, the Utility-Cost tradeoff space, which represents the performance of each design alternative, is conducted. The difference between PSBC framework and the existing methods is that strategy sampling is used to form a subset of the alternatives. The selected alternatives serve as representatives for the entire set. The reasons of strategy sampling for full set of alternatives are further explained in the section 3.3.2.

In the conceptual modeling phase, the SBC approach is adopted. Specifically, the design concept will be modeled by a set of design alternatives, which have been explored in the Utility-Cost tradeoff space. The fundamental problem is how to select a set of representative design alternatives to model the performance of the design concept. Various researchers are focused on this topic (e.g. Mattson and Messac 2003, Avigad and Moshaiov 2009). In this framework, Pareto Front Union (PFU) is used to select a representative design alternative. It can be generated as follows: first, the Pareto frontiers for different sets of design alternatives are found, with the goal of modeling SBC. Second, the union of the Pareto frontiers for all SBCs is found in order to further generate and evaluate the PSBCs. Different from the s-Pareto frontier (Mattson and Messac 2003), the simulation approach instead of the normal constraint method is used to generate Pareto frontier in this framework. This is because that the normal constraint method cannot explore the whole region. Omitting some points in the Pareto frontier in the early phase may generate suboptimal solutions. On the other hand, the simulation approach is an efficient way for two-dimensional tradeoff space. At the end of this phase, the union of the Pareto frontiers is generated, which is called PFU in this thesis. The bold lines in Fig 3.3 (a) are Pareto frontiers that are used to model PSBCs. The PFU is shown in Fig 3.3 (b).



(a)



(b)

Fig 3.3 (a) Modeling set-based concept by Pareto frontiers; (b) Pareto front union

In the concept selection phase, the optimal concept is finally determined. There are three major steps in this phase. First, PSBCs are compared one-by-one in order to eliminate entire dominated concepts. As illustrated in Fig 3.3 (a), the set of design alternative 3 is eliminated in the first step since it is totally dominated by set of alternative 1 and 2. Second, partly dominated concepts are left to further generate PFU. It should be noted that if only one concept is left after the first step, the selection phase can be completed. Obviously, the optimal concept is the dominate concept. However, if multiple concepts are left after the first step, further evaluation process is conducted. The performances of set-based concept are measured within specified boundaries in the objective space, namely a “region-of-interest” (RI). As illustrated by Mattson and Mattson (2005), the performances of set-based concept depend on the selected RI. A similar method, called “window of interest” (WOI), was suggested by (Avigad and Moshaiov 2010). Different from RI, WOI limits the search to a restricted region of the objective space. Our selection process builds on the RI method. The details of the improved RI for Utility-Cost tradeoff space are explained in the section 3.3.2.

3.3.2 Procedure Description

In the previous section, the PSBC framework is demonstrated. In this section, details of the main decision making process will be explained. More specifically, we focus on the concept selection and evaluation process.

One of the important parts is to identify a representative sample of design alternatives. Most of the existing work model the set-based concept using an entire set of design alternatives (e.g. Mattson and Messac 2005). However, we claim that it is problematic. The challenge is that it could be too expensive to simulate and evaluate the entire set of design alternative. Using a subset of the design alternatives to represent the performances of the entire set can save recourses. Random sampling of the entire set is used in the following numerical example (Section 3.4). The advanced sampling method need to be studied in the future.

The PSBC is modeled by Pareto frontier based on the subset of design alternatives. After one-by-one comparison, the performance of each concept needs to be further measured when multiple partly dominated concepts are left, as illustrated in section 3.3.1. Before continuing, it is important to specify several assumptions used in the proposed selection process:

- *Rational Decision*: The decision makers prefer high utility and low cost design concept.
- *Flexible Criteria*: The concept whose Pareto frontier has a larger surface area potentially offers more design flexibility than those with smaller Pareto surface. The concept with more design flexibility is assumed to be preferred (Mattson and Messac 2005).
- *Alternative Distribution*: The design alternatives in the Utility-Cost tradeoff space are evenly distributed.

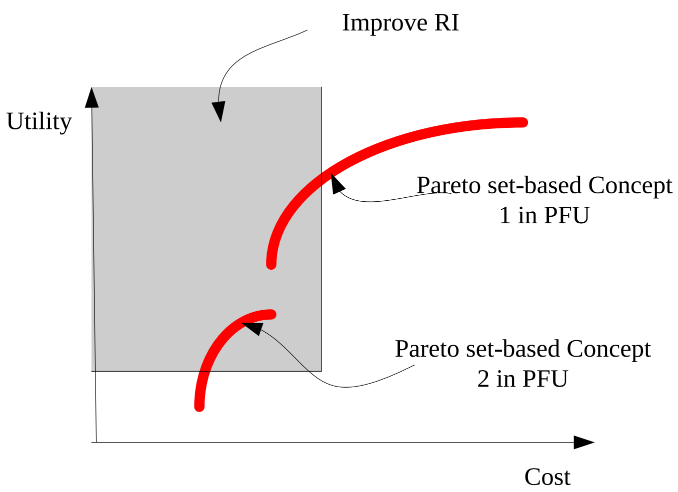


Fig 3.4 Pareto set-based concepts in the improved RI

Different from the multi-objective space, the Utility-Cost tradeoff space is a max-min space. The region of the design space that interests the decision makers is the area with high utility and low cost. Thus, the improved RI is an infinite region since high utility is preferred. The lower bound of the utility is specified by decision makers. Meanwhile, the up bound of the cost is determined depends on the system environment. Fig 3.4 illustrates the improved RI.

When the improved RI is selected, the design space is reduced to that region and only the PFU in the improved RI is considered. The performance of a concept can be evaluated by the area of each PSBC in the PFU, based on the flexible criteria assumption. Mathematically, the performance of the i^{th} concept G_i can be expressed as:

$$G_i = \int_{p_i} dp_w \Big/ \int_{p_w} dp_w \tag{3.3}$$

where p_w is the whole PFU; p_i is the PFU for the i^{th} concept in the improved RI. Under the alternative distribution assumption, the area of the PFU can be approximately measured by the number of design alternatives in the PFU. The performance of the i^{th} PSBC is:

$$G_i \approx {}^{N_i}\!/_{N_w} \tag{3.4}$$

where N_i is the number of design alternatives in the PFU from the i^{th} PSBC and N_w is the number of design alternatives in the whole PFU.

3.4 Numerical Example

In this section, a design problem of airport transportation system is used to illustrate the PSBC framework. Different transportation concepts for Chicago's international airport, which originally come from Nickel (2010), are compared. The purpose of the original problem in Nickel (2010) is to illustrate how to generate design alternatives by using Multi-Attributes Tradespace Exploration (MATE). The details of how to identify the system mission, the procedure of how to decompose attributes as well as the criteria of how to calculate cost are discussed in Nickel (2010). Although we use the same data from Nickel (2010), the research purpose is different. First, we simplify the problem by considering the problem from one perspective of the decision maker—private operator. In addition, our focus is to map the multiple objectives into two-measurement dimension (i.e. the desirable utility and the undesirable cost) and to visualize the concept selection process in the conceptual design phase.

In this numerical example, three major concepts, namely Express Service (ES), Bus Rapid Transit (BRT) and Blue Line Switch (BLS), are generated in order to provide a fast and reliable airport connection of Chicago. A number of feasible design alternatives are simulated for each design concept. The design alternatives that fall in the Pareto frontier of each design concept are used to model the PSBC. To further evaluate each PSBC, the union of the PSBCs is found. The optimality of the PSBC is discussed in different regions-of-interest. Section 3.4.1 describes the background information as well as the setting of parameters of this numerical study. Section 3.4.2 discusses the simulation results.

3.4.1 Problem Description

The background of this case study is that travelers are unsatisfied with the airport land connections in Chicago. Currently, two main routes link Chicago's main airport to downtown Chicago: the Kennedy Expressway and the rail Blue Line. Due to the frequent congestion in Expressway, the commuters as well as travelers to the airport cannot reach the airport on time in most cases. Meanwhile, the Blue Line stops 15 times on its way from downtown Chicago to the airport. It will take 50 minutes from downtown to the airport. To ensure Chicago's competitiveness with other global cities for conferences and business, a fast and reliable airport connection is needed.

Concepts Generation

Three major concepts are generated in this example:

- *Express Service (ES):* This concept would utilize the unused tracks of the Chicago commuter rail system: Metra. The new service could be operated reliably since it is a separate way for current express. However, a number of stations have to be rebuilt and significant costs are needed.

- *Bus Rapid Transit (BRT):* This concept would separate one lane of Kennedy Expressway for bus rapid transit. Capital costs of this concept are minor since only two bus terminals need to be built. The problem is that the traffic capacity of Expressway would be reduced.

- *Blue Line Switch (BLS):* This concept would use current Blue Line for a non-stop airport express. Meanwhile, the local buses and vans are used to provide better door-to-door service to former Blue Line riders, especially local riders.

Attributes and Design Variables

in the identification phase, decision makers define the attributes, which measure how well the objectives are met. In this example, the attributes are classified into two categories: desirable attributes and undesirable attributes. The desirable attributes provide utility, whereas the undesirable attributes present cost. According to the original problem, the main stakeholders who are expected to contribute to the funding of the airport express are the City of Chicago, the Chicago Transit Authority (CTA) and Private Operator. Different stakeholders may have different perspectives. To simplify the example, we make the decision just based on the perspective of Private Operator. The Private Operator is suggested to be charged with the management of the airport express. The attributes and design variables are elicited from Private Operator in the interview, as it stated in Nickel (2010). Table 3.1 shows the design attributes and their ranges for Private Operator.

Table 3.1 Attributes and range for private operator

	Attributes	Min (utility=0)	Max (utility=1)
Desirable Attributes	Quality of service	2	5
	Freedom to make changes	1	4
	Competition agreement	3	5
Undesirable Attributes	Operating cost	10000	0
	Concession payment	300	0

In Table 3.1, the “quality of service” measures how well the stakeholder group is catered to the users. Different users will have different criteria. For example, a business traveler may focus on the reliability and travel time, whereas a leisure traveler may prioritize the low price. “Freedom to make changes" demonstrates the ability of Private Operator in making operational changes without having to consult the CTA and City of Chicago. "Competition agreements" refers to the attribute that limit the CTA and the City of Chicago to run competing services on the Kennedy Expressway and Blue Line. In this case, a large number in the range means that the Private Operator has the high ability to restrain the competition with the airport express. For the undesirable category of Private Operator, operating cost and concession payment are the two important kinds of attributes. The "concession payment" is a one-time, fixed and certain payment, which the Private Operator will be charged with the management of the airport express (Nickel 2010). The calculation of "concession payment" and "operation cost" are provided in Nickel (2010).

Table 3.2 Decision variables for private operator

Design variables	Range	Measure
Fare level	[10,35]	$
Frequency	[5,20]	Headway in min
Travel time	[20,30]	min
Amenities	[1,5]	scale
Span of service	[16,24]	Hr/day
Freedom to make change	[1,5]	scale
Competition agreement	[1,5]	scale

Table 3.2 shows the decision variables in this example, while Table 3.3 shows the mapping relationships from design attributes to design variables. The mapping relationships are used to select the design variables that strongly influence the design attribute. The numbers in Table 3.3 indicates the relationship between the design attributes and the design variables. According

to Nickel (2010), a larger number indicates strong relationship. The actual model is based on the relationships as represented in Table 3.3.

Table 3.3 Mapping relationships from attributes to design variables

Design variable	Attributes				
	Quality of service	Freedom to make changes	Competition agreement	Operating cost	Concession payment
Fare level	9	0	0	0	0
Frequency	9	0	0	9	0
Travel time	9	0	0	3	0
Amenities	9	0	0	0	0
Span of service	9	0	0	3	0
Freedom to make changes	0	9	0	0	3
Competition agreement	0	0	9	0	3

The design variables could translate directly into attributes. For example, the quality of service attributes for the Private Operator is derived through an aggregation of the five factors: fare level, frequency of service, travel time, amenities and span of service. The value of the attributes should be normalized. After the desired/ undesired attributes are estimated, the utility and expense can be calculated using the Eq (3.5) and (3.6):

$$U_{DA} = \sum_{\forall a_i \in DA} w_i \frac{a_i - min(a_i)}{(max(a_i) - min(a_i))^{\gamma}} \tag{3.5}$$

$$E_{UDA} = \sum_{\forall a_i \in UDA} w_i \frac{a_i - min(a_i)}{(max(a_i) - min(a_i))^{\delta}} \tag{3.6}$$

where a_i is the i^{th} attributes, DA is the set including all the desired attributes, UDA is the set including all the undesired attributes, w_i denotes the normalized linear weighting factor for attribute a_i, γ and δ characterizes the shape of utility function. In this example, a diminishing return function (γ=1/2, δ=1/2) is used for the utility and expense functions.

3.4.2 Results and Discussions

For this case study, we simulate design alternatives for three design concepts via random sampling of the set of design alternatives. Forty thousand sets of design alternatives for each design concept are sampled, in order to describe the performance of the entire design concept. Utility is aggregated though the utility function (Eq 3.5) and represented on the y-axis, whereas the aggregated cost (Eq 3.6) is displayed on the x-axis. Fig 3.5 shows all the design alternatives in the Utility-Cost tradeoff space. The Pareto frontiers of each concept, called Pareto set-based concept (PSBC), are presented in Fig 3.6. Each of the PSBCs consists of all the design alternatives which provide the highest utility at a given cost level.

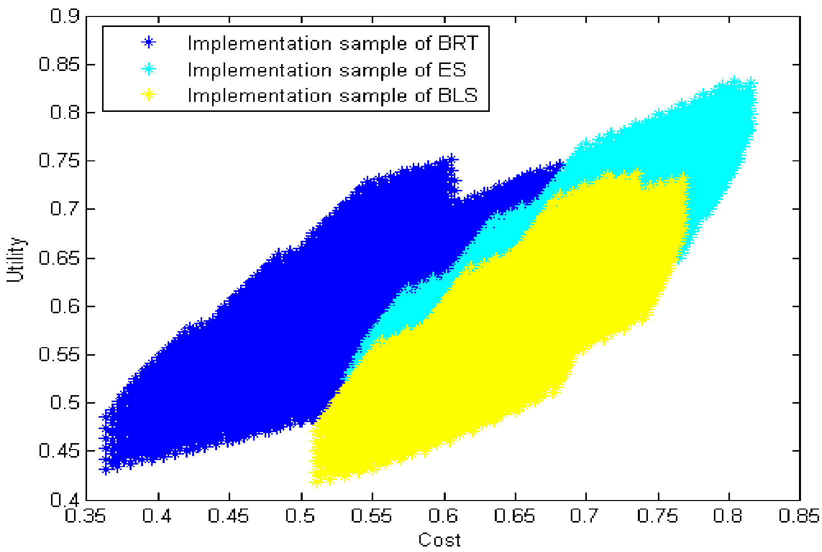


Fig 3.5 Design alternative samples of each concept

According to Fig 3.5 and Fig 3.6, the PSBCs of BRT and ES are partly dominated by one another, whereas the PSBC of BLS is totally dominated by the PSBCs of BRT and ES in this case study. The result indicates that at a same cost level, the concept of BLS provides less utility than either the concept of BRT or that of ES. Therefore, it is suggested that the concept of BLS is not a cost-effective design and can be eliminated in the first phase. To improve the accuracy of the result and justify the elimination, more Pareto sets for each design concept should be simulated. Moreover, the lower bound and upper bound of the confidence interval for each Pareto set should be further discussed and analyzed. Here, we mainly focus on illustrating the concept selection procedure.

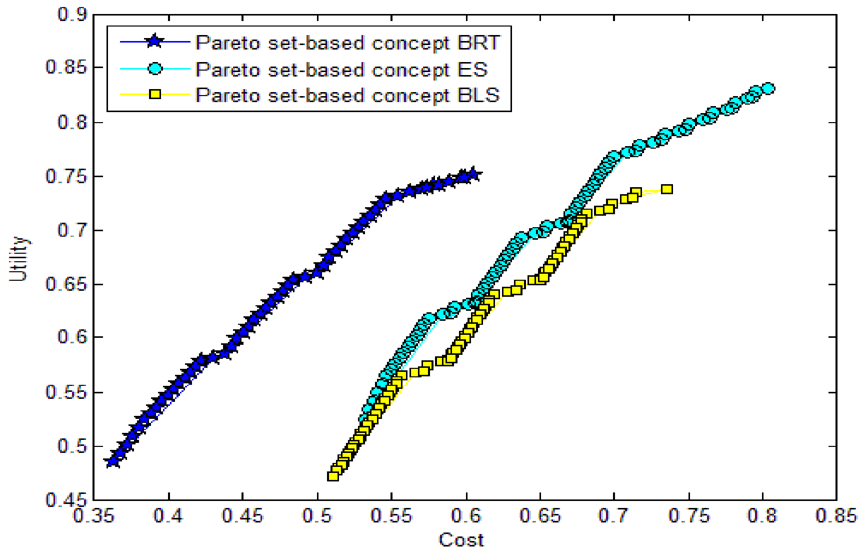


Fig 3.6 Pareto set-based concepts for BRT, ES, and BLS

In the second phase, the Pareto Front Union (PFU) is generated based on the PSBCs of BRT and ES. Fig 3.7 shows the PFU of this case study. In Fig 3.7, the PFU is made up by the PSBC of BRT when the cost is less than 0.65, whereas it is comprised by the PSBC of ES when cost is from 0.65 to 0.85. Fig 3.7 demonstrates two important features of this PFU. First, the PSBC of BRT has a large proportion in the PFU, compared to the PSBC of ES.

Second, although the total utility of the concept BRT is not as good as the concept ES, the concept BRT is the most cost-effective design when the stakeholders just have limited implementation cost. In contrast, since the concept ES can provide higher utility, it is the optimal design when the stakeholders have enough implementation resources.

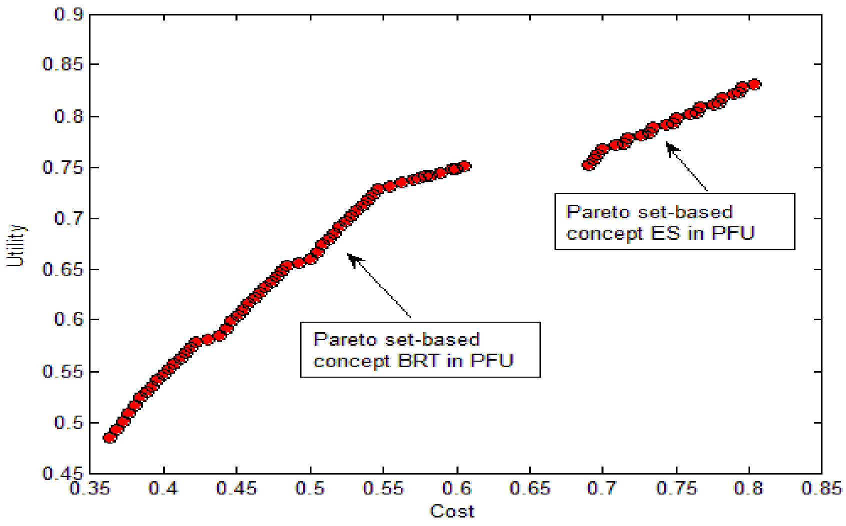


Fig 3.7 The Pareto front union for BRT and ES

Four different regions-of-interest (RI) are selected in this case study. The four RIs are specified in the early design phase, which are described by the boundary value of utility and cost in Table 3.4. The performance of each PSBC is calculated by Eq. (3.3).

Fig **3.8** shows an example and illustrates how to select an optimal concept in the regions of interest (RI_1). In

Fig **3.8**, 38% of the PFU is comprised by the concept BRT, whereas no design alternative from the concept ES is in the improved RI_1. Therefore, the optimal concept is BRT when decision makers are interested in the improved RI_1.

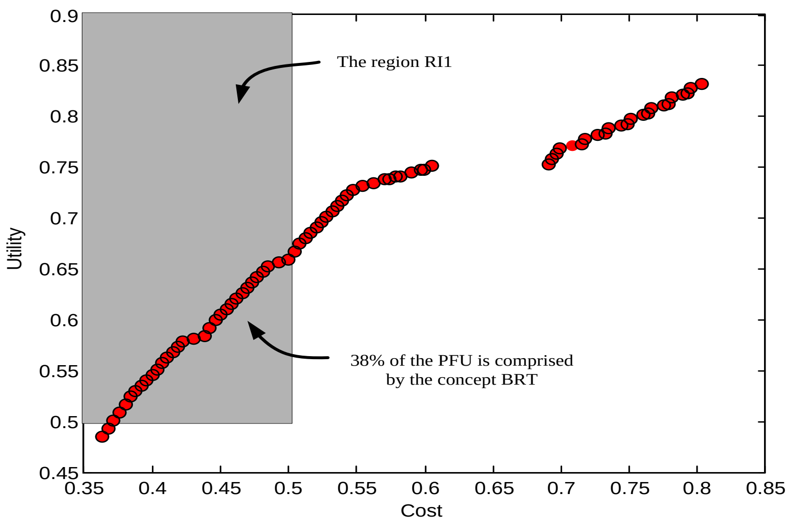


Fig 3.8 The concept selection in RI_1

Table 3.4 shows the optimal concepts in different improved RIs. Some observations can be obtained from Table 3.4. First, the optimal concept for decision makers depends on the selected region-of-interest. In RI_1, RI_2, and RI_4, the optimal solution is the concept BRT, whereas the concept ES is the optimal decision in RI_3. Therefore, it is important for decision makers to select a suitable region-of-interest according to a particular decision environment. Second, the decision makers, who prefer high investment as well as a high profit return, will prefer the concept ES in this case study. In contrast, the decision makers who have limited resources will prefer the concept BRT, since the implementation cost of this concept is lower than that of the concept ES. Third, the concept BRT will be selected with high probability when the region-of-interest is large. This is because that the PSBC of BRT has a larger proportion in the PFU.

Table 3.4 Improved RI and corresponding optimal concept

Improved RI	Boundary		Goodness of Pareto set-based Concept		Optimal Concept
	Utility	Cost	G_{BRT}	G_{ES}	
RI_1	>0.5	<0.5	0.38	0	BRT
RI_2	>0.5	<0.85	0.68	0.30	BRT
RI_3	>0.8	<0.85	0	0.13	ES
RI_4	>0.65	<0.75	0.32	0.16	BRT

3.5 Summary

In this chapter, a Pareto set-based concept framework is proposed. The proposed framework is built on the multi-attributes tradespace exploration and the set-based concept, in order to intuitively select design concepts in the conceptual design phase. The representation of the design concepts in a Utility-Cost tradeoff space offers a more efficient way for system designers to make their decisions. In the proposed selection framework, evaluation is not carried out in the full set of design alternatives. Instead, the Pareto frontiers are used to model the performance of the design concept. The designers can keep the competitive concept, eliminate the suboptimal concepts, and finally choose the specific design alternatives from the chosen design concept. A numerical example of airport transportation system is conducted. Several strategies for different decision makers and different decision environments are discussed. The example demonstrates that the PSBC framework could visually solve the problem of design concept modeling and selection regardless of the complexity of the system.

Chapter 4 Designing Flexible Engineering System with Multiple Exogenous Uncertainties

4.1 Introduction

Chapter 3 introduces a preliminary study for concept modeling and selection in the conceptual design phase. In this chapter, we will consider uncertainty and flexibility in generating the design concepts. Specifically, we are interested in the problem of identifying the elements in engineering systems that are most suitable for designing flexibility. The most suitable elements for designing flexibility are called as flexible design opportunities (FDOs) in this thesis. A sensitivity-based method for identifying FDOs is proposed in this chapter. The proposed method identifies FDOs based on whether the design elements are sensitive to the exogenous uncertainties or not. In other words, if the design elements are influenced by the exogenous uncertainties, it will be considered as a potential flexible design opportunity in the design process. In order to find the entire influence paths from exogenous uncertainties to system elements, an exogenous uncertainty searching algorithm and a flexible opportunity selection algorithm are presented. It quantitatively measures the sensitivity of each system element for engineering system design.

This work is inspired by the previous work Suh et al., (2007); however, it differs from the existing methods in several aspects. First, our work extends the existing methods by considering the multiple exogenous uncertainties simultaneously. Second, our work identifies both direct and indirect influences from exogenous uncertainties to system elements. These two important features allow designers to identify flexible design opportunities in a more realistic manner. Third, the proposed method provides a quantitative way to measure the sensitivity of system elements. The quantitative measurement could help designers to easily identify the most sensitive system elements. Therefore, it makes the designers to limit their resources in the selected system elements in the subsequent phase. The remainder of this chapter is organized as follows. Section 4.2 defines the concept of sensitivity and the quantitative measurement of sensitivity in this thesis. Section 4.3 presents the procedure of sensitivity-based method. Section 4.4 provides a summary of this chapter.

4.2 Preliminaries

Flexibility in engineering design enables a system to change easily in the face of uncertainty (Fricke and Schulz 2005). It makes the system has the ability to adapt to new environment and provides a good lifecycle performance when uncertainty occurs. However, designing engineering systems for flexibility is not easy. It may not be clear to designers and researchers to know when is the right time to exercise the flexibility, where is the right part of the system to enable flexibility. Designing flexibility in an unsuitable element may cost more. For instance, it could be a waste of resources to make a system element easier to change, while it is less related to the major sources of uncertainty and less likely to change. In this chapter, we aim to find the system elements that are susceptive to exogenous uncertainties for flexibility. This is because that the system elements, which are most sensitive and susceptive to exogenous environment, may have a high probability to change to adapt to the new environment in the future. Embedding flexibility in these elements will help to change the system. In addition, it will reduce the switching cost (i.e. cost associated to exercising flexibility, which changes the system form one state to another) often associated to adaptive mitigation strategies that are more reactive in nature. Therefore, the elements that are more susceptive to exogenous uncertainties are the suitable entities to consider flexibility.

The sensitivity-based method is proposed in this chapter. It attempts to find the most susceptive elements that need to be changed in order to adapt to the changes in the external environment. In this section, we will first formally define the concept of sensitivity in flexible engineering system design as well as the quantitative measurement of sensitivity.

4.2.1 Concept of Sensitivity

Directed graph is used to present the complex relationships between system elements and exogenous factors in the sensitivity-based method. Fig 4.1 shows a graph representation of a generic engineering system. Nodes x_i represent system element, which are within the system boundary. Exogenous uncertainties are presented by nodes ef_j in Fig 4.1. The directed arcs in Fig 4.1 represent the direct influence relationships. For example, the arc between exogenous uncertainty ef_m and system element x_3 means that the system element x_3 needs to be changed due to the effect of changing the exogenous factor ef_m.

Besides the direct influence relationships, system elements could also be indirectly influenced by the exogenous factors through other system elements in practice. As we discussed above, the system element x_3 is directly influenced by exogenous factor ef_m. In addition, it is also indirectly influenced by the exogenous factor ef_3 though the system element x_2. This is represented by a path from the exogenous factor ef_3 to the system element x_3 in Fig 4.1. The indirect influence relationship means that any change of the exogenous factor ef_3 may trigger the change of system element x_3 through the perturbation of the system element x_2. Although indirect influence relationship and direct influence relationship affect engineering system in different ways, both of these relationships are important to the designers. This is because that both relationships can trigger the changes of system elements. Therefore, the system element is sensitive to the exogenous factors by the direct or indirect influence relationship.

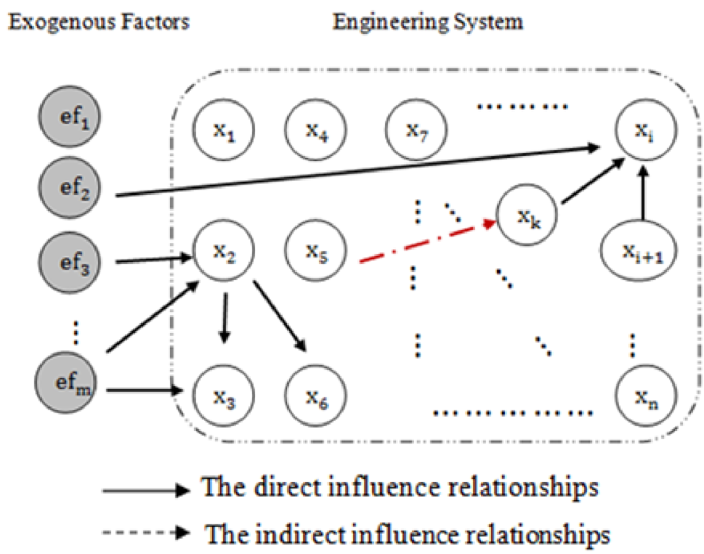


Fig 4.1 Engineering system with complex relationships

The sensitivity of system elements can be expressed mathematically. Consider a system that can be described using n system elements $X = \{x_1, x_2, \cdots\cdots x_n\}$. Meanwhile, exogenous factor of the system is analyzed, according to future uncertainties, the exogenous factor set is $EF=\{ef_1, ef_2 \cdots\cdots ef_m\}$. Let G be a directed graph, $G=(V, E)$ representing the system, where $V=X \cup EF$. If $(v_i, v_j) \in E$, where $1 \leq i \leq (n+m), 1 \leq j \leq (n+m), i \neq j$, there is an arc from v_i to v_j. Node v_i is a parent node of the node v_j. This arc also means that if a unit change Δv_i occurs, the element v_j will need to change to facilitate this perturbation in v_i. Therefore:

$$[(v_i, v_j) \in E\ ] \supset [(\Delta v_i \ \neq 0) \supset \left(\Delta v_j \neq 0\right)] \tag{4.1}$$

Definition 1: If $(\Delta v_i \ \neq 0)$, then $\left(\Delta v_j \neq 0\right)$. The node v_j is sensitive to the node v_i in this situation.

Let D_{ef_k} be the set that contains all the descendent node of ef_k, $k=1, 2, \ldots\ldots m$. D_{ef_k} is a subset of X. A descendent node of k^{th} exogenous factor is denoted as x_p^k, where $1 \leq p \leq n$, $x_p^k \in D_{ef_k}$.

Definition 2: A node $x_q \in X, 1 \leq q \leq n$, is sensitive to the exogenous factor ef_k if and only if $(ef_k, x_q) \in E$ or $\exists x_p^k \in D_{ef_k}$, $(x_p^k, x_q) \in E, p \neq q$. It can be mathematically described by Eq. (4.2):

$$\begin{aligned} &[(\Delta ef_k \neq 0) \supset (\Delta x_q \neq 0) \\ &\equiv \left[\left(\ ef_k, x_q\right) \in E\ \right] \vee [\left(\exists x_p^k, x_q\right) \in E \& (p \neq q)] \end{aligned} \tag{4.2}$$

We also define the sensitivity of each system element in a graphical manner. A system element is said to be *sensitive* in the neighborhood of a particular exogenous factor under any of the following two situations:

- ***Direct influence:*** The system element is directly influenced by an exogenous factor. In other words, there is an arc from the exogenous factor to the system elements in the directed graph (e.g. $ef_m - x_3$);
- ***Indirect influence:*** The system element is indirectly influenced by exogenous factors through another system element. In other words, there is a path from the exogenous factor to the system element in the directed graph (e.g. $ef_3 - x_2 - x_3$).

4.2.2 Quantitative Measurement of Sensitivity

The concept of sensitivity is defined as "direct/indirect influence is existed from exogenous factor to system element". The measurement of sensitivity for each system element can be defined as follows:

Definition 3: The sensitivity of each system element is measured by a number of exogenous factors that can affect it. It is not measured by the number of paths from the exogenous factors to a particular system element.

Let EF_q^* be a subset of EF that contains all the exogenous factors that have direct or indirect influence to system element x_q. It is defined by Eq. (4.3):

$$EF_q^* = \left\{ef_k \middle| (\Delta ef_k \neq 0) \supset \left(\Delta x_q \neq 0\right), \forall\, ef_k \in EF\right\} \qquad (4.3)$$

Definition 4: A system element x_q as being more sensitive, compared to other system element x_p, when x_q is influenced by more exogenous factors compared to x_p. It can be described as follows:

$$(C_q > C_p) \supset (S_q > S_p), \quad 1 \leq p \neq q \leq n \qquad (4.4)$$

where C_q counts the number of elements in set EF_q^*, S_q is denoted as the sensitivity of element x_q.

In Fig 4.1, there are two paths from exogenous factors ef_3 and ef_m to system element x_6. According to the definition of sensitivity in this thesis, the element x_6 is sensitive in the neighborhood of factors ef_3 and ef_m and the sensitivity of element x_6 equals to two. It should be noted that the sensitivity of system element x_3 is the same as that of system element x_6. This is because that element x_3 is only sensitive in the neighborhood of two factors ef_3 and ef_m, although there are three paths from exogenous factors ef_3 and ef_m to element x_3.

4.3 Sensitivity-based Method

In the previous section, the sensitivity of system element is defined. Moreover, it is quantitatively measured by counting the number of the influencing exogenous factors. The influence path from the exogenous factors to the system elements can be easily identified when a system has simple interconnection among system elements. However, in the real-world applications, a large number of system elements are usually required and the interconnections among the system elements are usually complex. Take Fig 4.1 for example, the influence paths from the factor ef_m to element x_i are difficult to find due to the complex interconnections. Procedures of sensitivity-based method is presented in this section, with the goal of finding entire paths from exogenous factors to particular system element efficiently as well as quantitatively measure sensitivity of each element.

4.2.3 Method Overview

Fig 4.2 describes the main procedures of the sensitivity-based method. This method assumes that external uncertainties can be analyzed in the initial design phase. A directed graph and design structure matrix (DSM) could be built after system elements and influence relationships are determined. Subsequently, the direction of the arc is reversed in the directed graph, in order to efficiently search influence paths. The next stage is to search the influencing path from a particular system element to exogenous factors using exogenous factor searching algorithm. The sensitivity of system element will be increased when an influence path is identified from system element to exogenous factor. The sensitivity of each system element is measured by the number of exogenous factors that affect it. This algorithm quantitatively and efficiently calculates the sensitivity of each system element. Finally, the FDOs are identified by the flexible opportunity selection algorithm, which compares the sensitivity of each system element. Here, the design opportunities for flexible options are the system elements are most sensitive to external uncertainty. Embedding flexibility for the selected FDOs can improve the system performance. This is evaluated in Chapter 6.

4.2.4 Procedure Description

Build Directed Graph and DSM representation

Building directed graph and DSM representation is a critical work in the procedure. It includes three main tasks: analyze exogenous uncertainties, determine system elements and identify influence relationships. The exogenous uncertainties are outside the control of designers, since they are from the external environment that the system is operated in. Based on de de Weck et al., (2007), exogenous uncertainties come from user context, market as well as political and cultural context. The examples of uncertainties are the number of competitors, the strength of competition, customer needs, duration of product life cycles, changing regulations and so on (Fricke and Schulz 2005). As for the system elements, the system should be broken down using technical domain knowledge. The anticipated goal of this process is to recognize and characterize the interconnected relationship among the system elements.

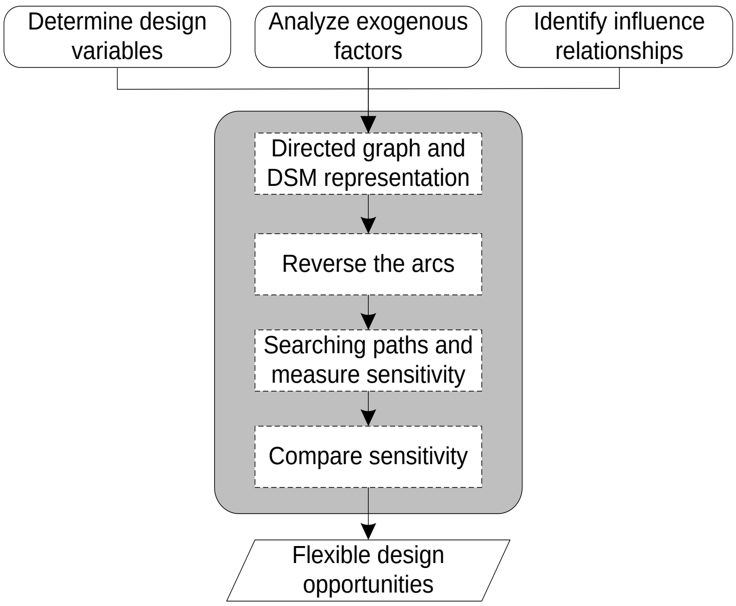


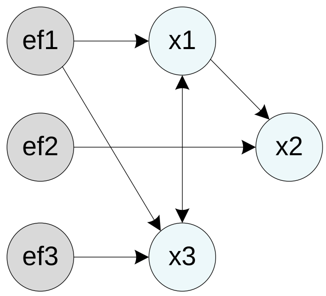
Fig 4.2 The procedure of sensitivity-based method

In order to ensure accuracy and integrity of the analysis, designers need to determine system elements, analyze exogenous factors and identify influence relationship as comprehensively as possible. These works are based on technology knowledge that should be extracted from existing research papers, history data or consultations with experts. It should be noted that two types of influence relationships are considered during this construction process: the influence relationships from exogenous factors to system elements and the influence relationships among system elements. Specifically, only the influence relationships, which are triggered from external environment, are considered during the construction process. A directed graph and DSM representation are built after all this information is collected.

Fig 4.3 shows an example of the directed graph and DSM representation for an engineering system. The interconnection relationships among system elements are presented by the arcs in the directed graph in Fig 4.3 (a). The DSM representation uses a matrix to reflect the system, see Fig 4.3 (b). Within the DSM representation, the column headings show triggered factors and the row headings show affected factors. The number 1 indicates connectivity between factors. It should be noted that the DSM representation here is a two-domain matrix. The first part in the left area examines the influence relationship between the "exogenous uncertainties" domain and the "system element" domain. The second part in the right area examines the relationships within the "system element" domain.

Reverse Arc Directions

Reversing the direction of the arc in the directed graph is another preparation work in this procedure. The goal of this activity is to improve efficiency for searching algorithm in the subsequent stage. The proposed searching algorithm, called exogenous factor searching algorithm, is based on depth-first search (DFS) algorithm. DFS is one of the techniques for traversing a graph. It starts at the root and explores as far as possible along each branch before backtracking (Cormen 2001). Formally, the algorithm starts at a root node and visits the first child node of the root node in a directed graph. Then it goes deeper and deeper until a goal node is found or until it hits a node that has no children. Then the search backtracks, returning to the most recent node that has not been visited. Take Fig 4.4 for example, if we need to measure the sensitivity of the node x_2, the algorithm will start at the root node (e.g. ef_1, ef_2 and ef_3) sequentially to find whether there is a path from ef_1, ef_2 and ef_3 to node x_2. Therefore, it traverses the graph three times.



(a)

Triggered factors

Affected factors		Exogenous Factors			System element		
		ef_1	ef_2	ef_3	x_1	x_2	x_3
System elements	x_1	1					1
	x_2		1		1		
	x_3	1		1	1		

(b)

Fig 4.3 (a) The directed graph; (b) DSM representation of a generic system

Although we can measure the sensitivity in this way, it is not an efficient way when there is a large number of system elements and exogenous factors. To quickly find the influence paths and measure the sensitivity, the direction of the arcs in the directed graph G is reversed in this stage. The corresponding graph *G'* is shown in Fig 4.4. In this case, the root nodes are changed to system element nodes. The proposed algorithm can start at the root node x_2 and goes deeper and deeper until a factor node ef_j is found. If a factor node ef_j is found, it shows that there is a path from factor node ef_j to element node x_i, and the factor node ef_j can affect the element node x_i. The sensitivity of the element node x_i will be increased by one. After traversing the graph, all factor nodes that could affect the system element x_i will be found.

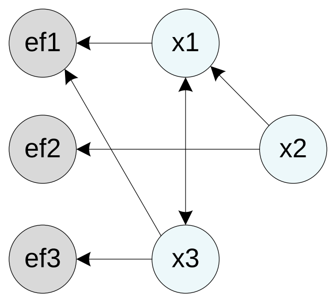


Fig 4.4 The reversed graph *G*

Search Exogenous Factor

The searching algorithm involves three inputs: 1) the graph *G'* with reversed arcs, 2) set of all system elements, and 3) set of all exogenous factors. The algorithm traverses the graph in a depth-first fashion and measures the sensitivity by counting the number of exogenous factors. In the exogenous factor searching algorithm, the loop starting on line 2 ensures that all system elements are visited. The *for* loop on line 4 marks all the elements as unvisited firstly. The algorithm starts from one of the nodes in the elements list. The *while* loop on line 6 traverses all child elements in both element list and exogenous list. Inside this loop and between the lines 9 and 11, the sensitivity of a node is increased when a factor node is visited. After traversing the whole graph, all exogenous factors which directly or indirectly connect to the element node are identified. Thus, by the end of *for* loop (line 16), the sensitivities of all elements can be identified.

Algorithm 1: Exogenous factor searching

Procedure:

```
1:    G' = reverse arc's direction of G
2:    for each node n in element list do
3:        Stack S =    // start with an empty stack
4:        for each node u in G', set u as unvisited
5:        push S, n
6:        while (S is not empty )do
7:            u = pop S
8:            if (u is not unvisited in G'), set u as visited
9:              if (u is a node in factor list) then
10:                 increase sensitivity value of n
11:            end if
12:            for each unvisited neighbor w of u in G' do
13:                push S, w
14:            end for
15:       end while
16:   end for
```

The flow chart of the exogenous factor searching algorithm is described in Fig 4.5. Take the elements in Fig 4.4 for example. If we would like to search the exogenous factors that connect with system element x_2, the algorithm first starts from the system element x_2 and then traverses the graph in a depth-first fashion. Assuming that the top arcs in the Fig 4.4 are chosen before down arcs, the algorithm will visit the nodes in the following order: x_2, x_1, ef_1, x_3, ef_3. The sensitive value of the system element x_2 is two, since two exogenous factors are found after the graph has been traversed.

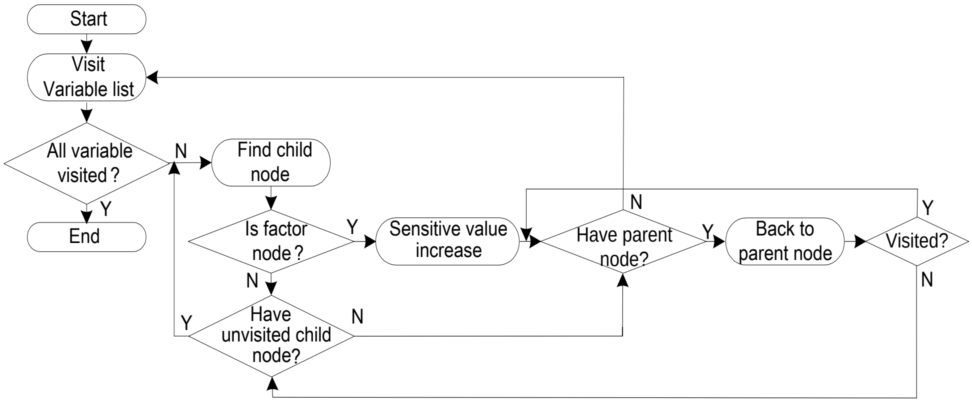


Fig 4.5 The flow chart of exogenous factor searching algorithm

<u>Select Flexible Opportunities</u>

The FDOs are identified after the sensitivities of all variables are measured. The flexible opportunity selection algorithm compares the sensitivities of each variable and finally selects the most sensitive variable. The input of this algorithm is the sensitivity value of each system element which can be obtained by exogenous factor searching algorithm. It starts from *for* loop (line 2) to make sure that the entire system element set could be compared. By the end of *for* loop (line 9), the sensitivity list contains the most sensitive elements. The elements which are selected in the sensitivity list are the potential opportunities where flexibilities can be added in the future design process.

4.3 Summary

In this chapter, a sensitivity-based method is proposed to identify where the flexibility should be added in a system. The system element x_i is sensitive to an exogenous factor ef_j when the exogenous factor ef_j directly or indirectly affects it. Specifically, the changes of exogenous factor ef_j can

Algorithm 2: Flexible opportunities selection

```
max sensitivity = 0
for each node n in element list do
    if the sensitivity value of n > max sensitivity then
        max sensitivity = sensitivity value of n
        clear sensitivity list and add n into the list
    else if sensitivity value of n == max sensitivity
        add n into sensitivity list
    end if
end for
return sensitivity list
```

trigger the changes of system element x_i. The system element that is influenced by a larger number of exogenous factors is more sensitive, compared to other system elements. The most sensitivity system elements are the potential flexible design opportunities, selected by exogenous factor searching algorithm and flexible opportunity selection algorithm.

The main contribution of this chapter is that: first, the sensitivity-based method measures the sensitivity of each system element with multiple exogenous uncertainties. It improves and extends the existing methods to generate flexible design concepts. Second, the sensitivity-based method extends DSM representation by considering the relationships from external uncertainty domain and system element domain. The extended DSM representation provides a clear mechanism to understand the complex interdependencies, which are not only within the system boundary but also outside it. Third, indirect influence relationships from exogenous uncertainties to system elements are considered in the analysis process. Consequently, the possible source of uncertainty for particular system element could be fully investigated. However, the sensitivity-based method also has limitations. Only one selection criterion (i.e. sensitivity) is considered in the evaluation process. In the real world, many factors may affect the results, such as the triggering probability that how likely exogenous uncertainty may affect system elements and the switching cost of changing system elements. All these factors are discussed in Chapter 5.

Chapter 5 Change Propagation Management in Flexible Engineering System Design

5.1 Introduction

In Chapter 4, a sensitivity-based method is proposed to generate flexible design concept by explicitly considering uncertainties. It analyses the interconnection among the system elements by using the Design Structure Matrix (DSM), and identifies the flexible design opportunities by considering both direct and indirect influence relationships with multiple exogenous uncertainties. Compared to traditional rigid methods, embedding flexibility in the selected opportunities could increase the performance of the system over the long term (Evaluation case study is illustrated in Chapter 6). However, sensitivity-based method simplifies the operating environment by making some assumptions, such as the triggering probability and switching cost of each system element are assumed to be the same. In this thesis, triggering probability is defined as the probability that a change in the design of one element will lead to a change in a neighboring element. Likewise, switching cost is defined as the cost of switching from one state of a design to another. Another assumption is that there will be no change after exercising a flexible option in future. These two assumptions are not realistic situations in the engineering system design.

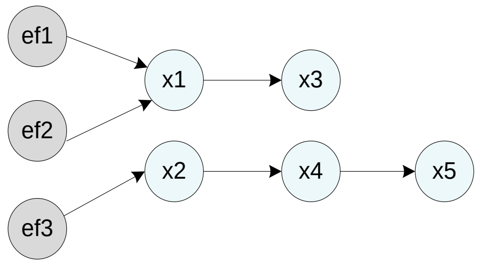
The goal of this chapter is to remove the assumptions in Chapter 4 and provides a more realistic modeling. Specifically, this chapter addresses the following research question: "How to model the indirect change propagation and predict its potential effects in the initial design phase, with the goal of selecting suitable system elements for designing flexibility?" A novel methodology is proposed to identify the most crucial and valuable design opportunities for embedding flexibility in an engineering system. The proposed methodology extends the engineering systems matrix (ESM) method to capture complex dependent relationships between system elements from multiple domains. It further integrates Bayesian network theory and CPM method to effectively model the complex change propagation, and to predict the effects when certain elements in the system need to be changed. Overall, the proposed methodology selects and ranks potential design opportunities by considering multiple uncertainties, change propagation phenomenon and complex interdependency that exist among the elements of such complex system. Compared to existing methods, the proposed methodology limits and reduces the number of design concepts that decision makers have to generate and evaluate before a detailed design phase and implementation.

5.2 Challenges for Realistic Modeling

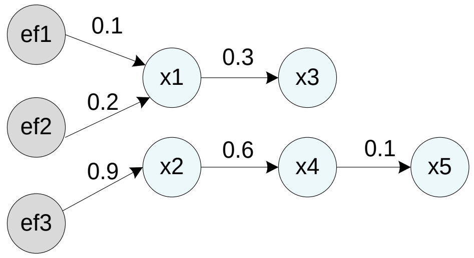
5.2.1 Triggering Probability and Switching Cost in Flexible System Design

In the sensitivity-based method, a directed graph and DSM representation are used to represent the interdependencies between system elements. In order to simplify the analysis process, an arc from one element to another in the directed graph means that the change of this element will certainly trigger the change of the other one. And the degree of all the relationships is assumed to be the same. However, in practice, certain information about this influence relationship within complex systems is difficult to obtain, especially in the initial design phase. Instead, only a probability distribution of the influence relationship can be identified from historical data or experienced experts. Therefore, the arcs in the directed graph can only represent a possible chance to trigger the change in the future. Counting the number of exogenous factors which have an indirect influence path or a direct arc to the system element is not an effective way to select flexible design opportunities. This is because that it cannot guarantee the optimal solution in some circumstances. In addition, the relationships between the system elements may have different degree of dependencies. For example, the government strongly controls the strategy for a company by issuing new policies and regulations. On the other hand, the operation and management of the company cannot control government's decision. The degree of dependency between the system elements should be taken into account, since efforts may be wasted for weak links.

Fig 5.1 (a) shows a graph representation of a generic engineering system. According to the influence relationships represented in the directed graph, system element x_1 and x_3 are affected by two exogenous factors, while system element x_2, x_4 and x_5 are affected by only one exogenous factor. After the analysis of sensitivity-based method, the system element x_1 and x_3 will be selected to embed flexible option, since it is more sensitive to the external environment. Although the sensitivity-based method is an intuitive way to find the flexible opportunities, it cannot guarantee the solution if the degree of dependency is not considered.



(a)



(b)

Fig 5.1 Graph representation of a generic system with or without triggering probability

Fig 5.1 (b) shows similar influence relationships within the system but with the triggering probability considered. The number added above each arc in Fig 5.1 (b) shows the triggering probability, which represents the degree of dependency between the system elements. The higher the number is, the stronger the dependence exists between the system elements. For example, in high-speed rail system, the government could strongly control the strategies, operation process and the train/track design of the manufacturing industry by issuing a new policy and regulation. Therefore, the triggering probability, which represents the probability that the manufacturing industry will change triggered by a change of the government policy, is assigned as a large number. On the other hand, the operation and management of manufacturing industry—i.e. the number of trains produced annually, the type of the train produced and the selling price of the train, may influence the decision of the government agency. However, this impact cannot control government's decision and the way to influence the decision is not clear. Therefore, the corresponding triggering probability is assigned as a small number.

The triggering probability is one of the important factors to estimate the susceptive of system elements. For example, if exogenous factor ef_3 is changed then system element x_2 need to change with 90% probability and a stronger relation is shown between these two factors. In Fig 5.1 (b), system element x_1 is influenced by two exogenous factors with low triggering probabilities (In this case, the triggering probabilities are 10% and 20% respectively). The triggering probability that system element x_1 will change in future due to the overall impact of both exogenous factors ef_1 and ef_2 is 28% (The triggering probability is mathematically calculated as OR relationship, since the triggering probability from ef_1 to x_1 and triggering probability from ef_2 to x_1 are in different path). On the other hand, system element x_2 is impacted by only one exogenous factor with 90% triggering probabilities. In this circumstance, system element x_2 will change in the future with higher probability than that of system element x_1. Therefore, it is more susceptive to external environment and suitable to embed flexibility in the initial design phase. The result is different with the discussion of sensitivity-based method. This example shows that estimating the susceptive of each system element should take into account the effect of triggering probability.

Another significant factor in the initial design phase is the switching cost. The switching cost of each system element may be different in the real world. In flexible engineering system design, system element with high switching cost requires special attention, even though the triggering probability of this system element is low. This is because that the total cost will significantly increase if changes occur in the future. Therefore, selecting flexible design opportunities without information of switching cost may also lead to suboptimal solutions.

5.2.2 Change Propagation for Flexible Option

Within complex engineering systems, system elements are closely linked with each other. A simple change of one system element may not only trigger the change of neighboring system elements, but also propagate the impact to other non-adjacent system elements. For example, in the high-speed rail system, the block length (i.e. distance between signals) is designed based on the braking distance, since the block length must be long enough to enable the train with the longest braking distance operating on the track to stop. Furthermore, the braking distance is determined by the characteristics of the trains, such as the total weight, the design speed and the braking ability of the train. Therefore, changing one parameter of the train may propagate the change to a large portion of the system, and may cause impact to the whole system. This phenomenon is called as change propagation in this thesis.

The feature of change propagation makes identifying FDOs become a challenging problem. In the sensitivity-based method, change propagation from exogenous uncertainties to system elements is analyzed, by considering the indirect influence relationships. Although the sensitivity-based method is a useful and straightforward method for identifying candidates of FDOs, it still may not guarantee the “best” FDOs since it assumes no change will occur when flexibility is exercised in the future.

As we discussed before, flexibility is "the ability but not obligation, to change the system as uncertainty unfolds in future". The anticipated performance of adding flexible options in the selected opportunities is to make the system change easily in future if it is required. Based on the definition, using such flexible option in the management and operation phase may cause changes of system elements and also have effect of change propagation. If this effect of change propagation is huge, the designed element is not a "best" FDO even though it has high value of sensitivity. The reason is that huge switching costs are needed during the system management and operation process, once the flexible option has been exercised. In contrast, robustness which is defined as "the ability to be insensitive towards the changing environment" may be a more suitable design strategy in such circumstance. This is because robustness may provide tolerance margins which can absorb the change as well as generate change propagation.

Therefore, the candidates of flexible design opportunities which are selected by sensitivity-based method need to be further analyzed and classified, with the goal of avoiding huge switching cost and bringing significant improvement for engineering system. In this chapter, change propagation of exercising flexibility is considered in the proposed method, to identify FDO.

5.3 Risk Susceptibility Analysis

The methodology begins from analyzing a specific design problem and developing a quantitative performance model (Section 5.3.1). Subsequently, the complex dependences between system elements and major uncertainty drivers should be identified (Section 5.3.2). Using the identified information, such as the system-level dependency and the cost of switching from one state of design to another, the potential flexible design opportunities should be selected (Section 5.3.3). In the final step, the flexible strategies are generated based on the opportunities which are selected in the previous step. The value of exercising the flexibility is calculated and compared based on real option analysis (Section 5.3.4). The procedure of the methodology is summarized in Fig 5.2.

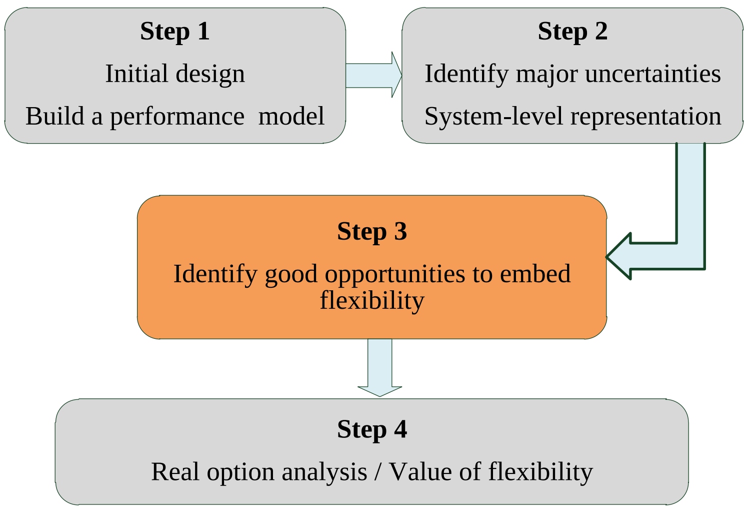


Fig 5.2 A methodology to generate flexibility in engineering systems

Fig 5.2 shows the four-step procedure. A variety of method and tools may be used in each of the steps (e.g. simulation-based analysis and binomial lattice analysis are two ways to value flexibility in step 4). The main contribution of the proposed methodology is to extend the existing methodologies and tools in the step 3. Specifically, the proposed methodology focuses on the identification process. It improves the existing analysis by considering indirect change propagation phenomenon in the identification process. In addition, the potential effects for exercising flexibility in a design are taken into account. Third, multiple uncertainties are modeled simultaneously in identifying the FDOs. These extensions will help the designers model the change propagation phenomenon in a more realistic way. The proposed methodology also provides a general procedure to screen out a smaller number of candidate elements for flexibility, and therefore save resources in the further evaluation process.

5.3.1 Step 1: Initial Design

The first step focuses on analyzing a design problem, understanding the main cost and revenue components of the design problem, and generating a discounted cash flow (DCF) model. Here, the DCF model is analyzed based on a set of deterministic point forecasts of uncertain factors, such as customer demand and requirement. Using this model, the lifecycle performance--i.e. net present value (NPV) of each candidate design concepts can be calculated. In addition, the best design concept with better lifecycle performance is selected. The selected design concept serves as a benchmark design. It will be further compared with the flexible design concepts in Step 4, to determine the value of flexibility.

5.3.2 Step 2: Dependency and Uncertainty Analysis

The second step focuses on modeling and representing a complex engineering system at a systems-level. The ESM methodology is used for characterizing the source of uncertainties and interdependencies of the system elements. The ESM models engineering system using an adjacency matrix and represents the direct dependent relationships between the neighboring system elements. It captures the dependent relations of system elements from multiple domains (i.e. function domain and stakeholder domain), thus providing a holistic view of the engineering system for designers. The major sources of uncertainty are generally from the system drivers' domain in the ESM model, including the economic, political, social and technical influences that impact the characteristic of components in the system (Bartolomei et al., 2012).

Here, the ESM methodology is extended to model the engineering system by considering how likely one element will change due to a change in neighboring element. Specifically, we aren't only modeling whether a dependent relation exists or not, but also examining the degree of likelihood of such dependent relationship. The relation and the degree of dependency are represented using a triggering probability, which is defined as the probability that a change in the design of one element will lead to a change in a neighboring element. Besides the triggering probability, the prior probability – showing how likely an uncertain scenario will occur in the future – and the switching cost – representing the cost of system elements related to the change – are analyzed. All domain information for constructing the system-level representation is extracted based on experts' knowledge and historical data. The likelihood of change can be elicited using standard probability elicitation techniques (Morgan and Henrion 1990).

5.3.3 Step 3: Flexible Design Opportunities Identification

The third step is the main part of our methodology. It involves three tasks: modeling complex interdependencies, predicting risk susceptibility of each system element, and recommending suitable system elements.

Bayesian network model development

As we discussed previously, a simple change of one element may trigger a change of other elements with either direct or indirect relationships. To holistically model this complex change mechanism, both of the change effect to the neighboring elements and the non-adjacent elements should be taken into account in the analysis process. In this these, such change impact is measured quantitatively by a *conditional probability*, defined as the change probability of one element given the change of other elements with either direct or indirect dependent relationships. This *conditional probability* indicates how likely one element will change if other elements are changed.

Complex interdependencies of system elements are modeled using a Bayesian network methodology. The system elements, which are analyzed in the ESM matrix, are represented as nodes, and the direct relationships between elements are modeled as edges in the Bayesian network. The prior probability and triggering probability are used to construct the conditional probability table (CPT) for each node in the network. Once the Bayesian network has been constructed, the combined *conditional probability* of each element can be fast inferred. This is because that there are a number of efficient inference algorithms for performing the probabilistic updating, providing a powerful function of predicting and reasoning (Pearl 2000). In addition, the designers can easily set values to model the changes. For example, the major uncertainties, like demand or selling price can be set to a certain threshold value, or set the combination of these values. These settings may trigger changes of the system elements and then are propagated through the network, producing a new probability distribution over the remaining elements in the network, showing the what-if scenarios of the impact of change. The characteristic of each system element that shows the sensitivity to the uncertain scenarios can be easily identified. A detailed example of inferring the combined probability using the Bayesian network is described in section 4.

Risk Susceptibility Prediction and Measurement

The risk susceptibility of each system element if a change is triggered and propagated within the system is predicted. The risk susceptibility here is measured by the conditional probability, which is inferred using the Bayesian network, and the switching cost, which is extracted from the Step 2. In the risk susceptibility prediction process, the switching costs are normalized with respect to the maximum value of each system element. The risk measurement methodology used here is adapted from the risk management theory and change prediction method (Clarkson et al., 2004).

First, the risk received by each system element when a change is triggered by uncertainties is measured. This risk is denoted as $R_{s_i}^{Received}$, and is calculated as:

$$R_{s_i}^{Received} = P_{s_i|\forall\, u_j \in D^k} C_{s_i} \tag{5.1}$$

where s_i represents the i^{th} system element, D^k is a set of uncertainties for scenario k, u_j is one of the uncertainties in D^k, and C_{s_i} is the switching cost for the system element s_i. The term $P_{s_i|\forall\, u_j \in D^k}$ represents the probability that system element s_i will change caused by all uncertain factors in scenario k, via both direct and indirect links. This kind of probability is the conditional probability in this paper and it can be inferred by Bayesian network model. In other words, $R_{s_i}^{Received}$ indicates the degree of the risk received by system element s_i, due to the impact of uncertainties.

The second measurement is to predict the risk caused by system element s_i, if system element s_i is changed. Let us assume that a flexible option is embedded in system element s_i in the initial design phase. If one implements a flexible option to respond to uncertainty, the system element s_i will change and this change may further propagate to other child nodes. The problem is how to measure the risk on these child nodes downstream, due to a change of system element s_i upstream. This can be calculated as:

$$R_{s_i}^{Generated} = \sum_{s_j \in D_{s_i}} (P_{s_j|s_i, \forall u_j \in D^k} - P_{s_j|\forall u_j \in D^k})\, C_{s_j} \tag{5.2}$$

where s_j represents a child node of system element s_i, $s_i \neq s_j$, D_{s_i} is a set of system elements which contains all the child nodes of system element s_i, $P_{s_j|s_i, \forall u_j \in D^k}$ is the conditional probability of a change for system element s_j given a change in system element s_i under scenario k, $P_{s_j|\forall u_j \in D^k}$ is the conditional probability of a change for system element s_j only conditioned on the uncertainties in scenario k.The subtraction here represents the increased probability of each child node, due to a change of system element s_i. $R_{s_i}^{Generated}$ indicates the degree of the risk generated by the system element s_i, when the flexible option is implemented.

Recommendations

This section discusses how recommendations can be provided based on the risk susceptibility computed in the previous section. For ease of visualization, the risk susceptibility of system element can be plotted in a chart as shown in Fig. 5.3. The chart can be divided into four regions. And the recommendation analysis is discussed as follows:

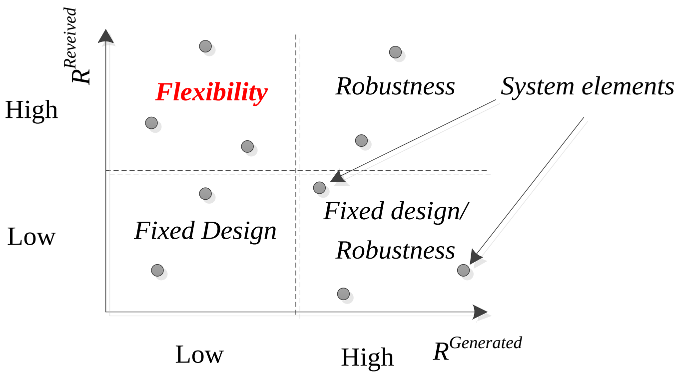


Fig. 5.3 Risk susceptibility of system element

- The system elements that fall on the lower left of the chart have relatively low risk susceptibility $R_{s_i}^{Received}$ and $R_{s_i}^{Generated}$. It means that these system elements are the least critical elements. This is because that they are unlikely to be changed in the future to response the major uncertainties. Even though it is required to change, only small switching cost is needed and small influence to other system elements is incurred. Hence, fixed design is suitable for these elements.
- The system elements that fall on the upper left of the chart have high $R_{s_i}^{Received}$ and low $R_{s_i}^{Generated}$. It implies that these system elements are likely to be changed and the impact of implementing the change will be high. It also represents that it may not cause significant impact to the whole system if a change occurs for such elements. Therefore, these elements should be made easier to change to save the switching cost in the future. This can be accomplished by embedding flexibility.

- The system elements that fall on the upper right of the chart have high $R_{s_i}^{Received}$ and high $R_{s_i}^{Generated}$. Similar to the elements in the upper left, these elements are also susceptible to uncertainties. On the contrary, a change of system element s_i may further amplify the change and generate more risk to the system. Therefore, these elements should be recommended to reduce the likelihood of change to avoid propagating further changes to others. Different from the flexibility, robustness handle uncertainties without changing the architecture of the system (Jugulum and Frey 2007). Hence, it is suitable for these elements.
- The system elements that fall on the lower right of the chart have low $R_{s_i}^{Received}$ and high $R_{s_i}^{Generated}$. It suggests that these elements are unlikely to change and the costs for implementing the change are small. However, if a change occurs, a significant risk will be generated to the whole system. Therefore, these elements should be considered robustness to reduce the likelihood of change. Also, they should be analyzed whether it is worth to embed robustness, since this robust option may unlikely to exercise in the future. The fixed design and robust design should be further evaluated based on the real situations.

The change propagation index (CPI) methodology by Suh et al., (2007) inspires the risk susceptibility index (RSI) proposed here, calculated via following equation:

$$RPI_{s_i} = R_{s_i}^{Received} - R_{s_i}^{Generated} \tag{5.3}$$

Based on the discussion above, it can be reasoned that the higher RSI_{s_i} is, the more suitable the corresponding system element is to embed flexibility.

5.3.4 Step 4: Flexibility valuation

The fourth step focuses on embedding flexibility in the selected design opportunities and quantitatively determining the benefit of flexibility. The outcome of this step would help designers determine whether the flexibility is worth the additional cost and design effort. The Monte Carlo simulation model is used in this step to generate stochastic scenarios, run all these scenarios simultaneously, and lead a distribution of possible performance outcomes. The lifecycle performance of the flexible design and the benchmark design (e.g. expected NPV) are calculated for thousands of future scenarios. The difference between the expected NPVs is the value of flexibility, which indicates the benefit of considering flexibility and uncertainty in the design. The reasons for choosing the Monte Carlo simulation model to value flexibility are as follows: 1) the uncertainty sources could be explicitly modeled; 2) the decision rules that characterize how managers would respond to uncertainty drivers could be easily integrated. Details of the Monte Carlo simulation model can be found in de Neufville et al., (2006) and de Neufville and Scholtes (2011).

5.4 Summary

This chapter proposes a methodology to identify valuable opportunities to embed flexibility in complex engineering system design. It extends the sensitivity-based method by considering triggering probability, switching costs as well as risk of change propagation for generating flexible design concept.

This methodology integrates Bayesian network methodology into the engineering system design, and effectively models complex change propagation within multiple domains of an engineering system. It builds upon and improves existing methodologies, which only consider direct neighboring relationships in the generation of flexible design concepts. The proposed methodology selects and ranks a set of system elements by predicting and analyzing the risk of change propagation. The ranking information of system elements limits the number of flexible design concepts to analyze at an early conceptual stage, in contrast to other concept generation methods available in the literature. Furthermore, the ranking information provides clear guidance to designers and decision-makers, especially when they have limited analytical resources available.

Chapter 6 Case Study 1: High-Speed Rail System Design

6.1 Introduction

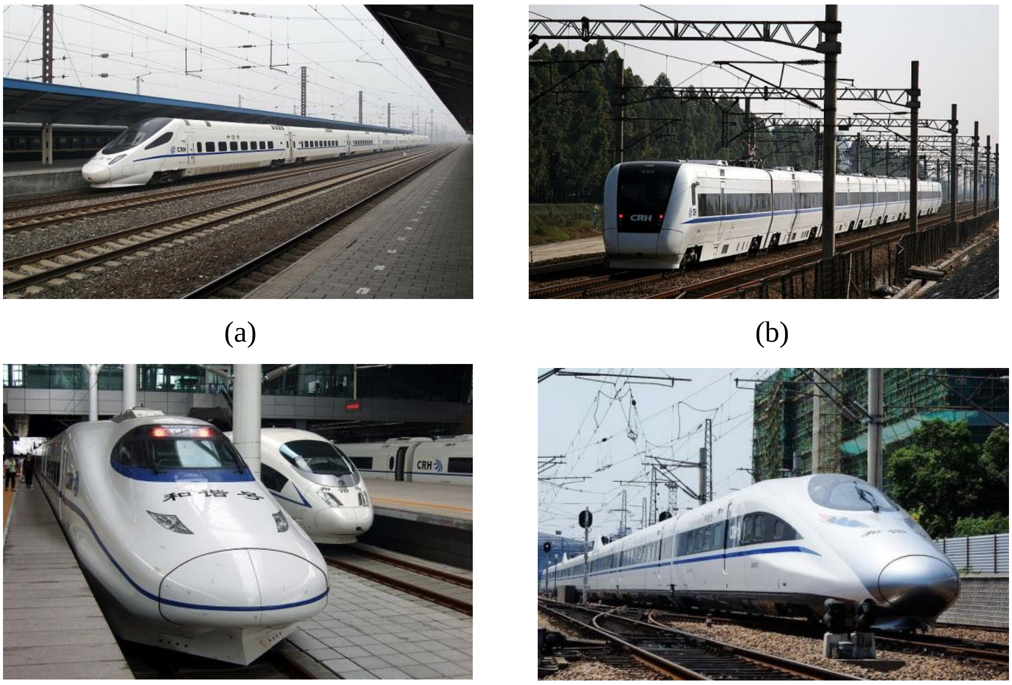
The purpose of this chapter is to illustrate an application of the sensitivity-based method and evaluate the performance of this method. The sensitivity-based method is applied and evaluated in a high-speed rail (HSR) system. The multiple exogenous uncertainties of HSR system are first identified and discussed in this case study. In addition, the complex interconnections among various sub-systems are analyzed. The flexible design opportunities for HSR system are selected by sensitivity-based method step by step. Flexible design strategies are generated based on the selected opportunities and then compared with an inflexible design strategy. A simulation method, which is proposed by de Neufville et al., (2006) is used in this case study to value the flexibility and verify the sensitivity-based method.

It should be noted that this case study focuses on the subsystem-level analysis. It means that we just break down the system into subsystems rather than parameters. The reason is that it is difficult to identify complex interconnections in detail, since designers could rarely acquire in-depth knowledge about highly break down system in the real world. In addition, such detailed analysis is tedious and time-consuming. Once we identify flexible design opportunities in subsystem-level, we can limit our resources to further analyze design parameters if it is required (Chapter 7 presents an example in a parameter-level analysis).

The following section 6.2 introduces the motivation for choosing an HSR system as the application domain, including the discussion of the characteristic of the HSR system. Section 6.3 demonstrates how the sensitivity-based method is applied to identify flexible design opportunities for HSR system. Section 6.4 generates design strategies and develops economic models. Section 6.5 compares the flexible design strategies with inflexible design strategies and discusses the results. Section 6.6 summarizes this case study.

6.2 Characteristics of HSR System

With the increasing movement of people at the local, regional, national, and international levels, a demand on transportation systems has increased. High-speed Rail (HSR) system is one of the transportation systems which fit the medium-distance travel market—too far to drive and too short to fly. By providing comfort and safety service as well as competitive travel time, HSR system is developing rapidly and increasing gaining worldwide attention (Givoni 2006). At present, HSR system has successfully operated in Japan, France, Germany, China and other countries. For instance, China has an HSR network about 9676 km (Railway technology 2011). The high-speed trains have transported 600 million passengers since its introduction on April 18, 2007, with an average daily ridership of 237 thousand in 2007, 349 thousand in 2008, 492 thousand in 2009, and 796 thousand in 2010 (Ministry of railways of China 2011). Fig 6.1 shows some train-sets in China.



(a) (b)

(c) (d)

Fig 6.1 (a) A China Railways CRH5 train-set; (b) A China Railways CRH1 train in Guangzhou; (c) A China Railways CRH2C (left) and a China Railways CRH3C(right) train in Tianjin; (d) Chinese designed CRH380A train. (The original images are downloaded from http://en.wikipedia.org/wiki/High-speed_rail_in_China)

HSR system has some challenges in the development planning process:

- *Long lifecycles*: the typical lifecycle of an HSR system easily spans several decades. For example, the Beijing-Shanghai high-speed railway line, which started on April 18 2008, was designed for 100 years (Railbbs 2011).
- *Large capital investment*: development of an HSR system requires large capital investment. For example, the total investment for Beijing-Shanghai high-speed rail is 220.94 billion Yuan (Railbbs 2011).
- *Multiple exogenous uncertainties*: HSR system operates in a changing environment. The change is either from customer requirements or technical innovation. A key challenge for an HSR system design is to

take full consideration of future uncertainties while ensuring that no degradation of safety.

- *Complex interconnections within the system*: HSR system is built by various sub-systems, such as train-track interaction system, signal system and aerodynamic system. Development plan not only requires the design technical knowledge within the sub-system domain but also an understanding of the interconnection among sub-systems.

Because of these design challenges, the HSR system is a representative example within complex system engineering. In this chapter, a case study on the design of a hypothetical HSR system is presented, with the goal of illustrating how to use the sensitivity-based method to effectively identify flexible design opportunities.

6.3 Application of Sensitivity-based Method

6.3.1 Initial analysis

Key Exogenous Uncertainties

A number of system considerations and functional requirements should be used in evaluating HSR systems. According to Zayed et al., (2008) and Whitford and Karlaftis (2003), these system considerations and functional requirements include average speed, travel demand, schedule performance, ride quality, noises, safety, energy conversion efficiency, actual travel time, reliability and so on. The criterion of these performances may change in the future, due to changing customer requirement or technical innovation. In order to fit and adapt new criterion of these performances, some system elements need to change correspondingly. Thus, changing these functional requirements are the main sources of exogenous uncertainties affecting the HSR system in the future. For example, the average travel speed of China's rail is only 48.1km/h before 1993. During 1997 to 2007, the speed of China's train increased six times. After 2007, the speed of passenger trains went up to 200~250km (Ministry of railways of China 2009). This example shows that the functional requirement—travel speed is not a constant during the lifecycle of HSR system. Some system elements, such as curve design as well as accelerate and decelerate ability design should be changed accordingly to fit the increased travel speed. In terms of these exogenous design uncertainties, it is difficult to finalize the best choice of design. Adding flexibility in the related system elements can make HSR system change easily in the future.

While the functional requirements discussed above are all important, this case study will focus on five critical requirements. They are travel demand, ride quality, actual travel time, reliability, and energy conversion efficiency, as defined in Table 6.1.

Table 6.1 Exogenous uncertainty of HSR system

Exogenous Factors	Description
Travel demand	Predicted number of passengers in one year. It is growing as the population expands in a particular region
Ride quality	Comfortability of passenger's travel experience
Actual travel time	The travel time for passenger between origin and destination
Reliability	Ratio between the number of on time arrival train and total arrival train.
Energy conversion efficiency	System design efficiency with respect to energy consumption

The reason for selecting these functions as the source of exogenous uncertainties is that these five features are the most important features of the HSR system. From the history, the requirements for these features are changed and they affect the HSR design. For example, in order to allow trains to travel somewhat faster as well as meet the particular travel demand, shared-use strategy for today’s track design is an excellent solution (Nash 2003, Peterman et al., 2009). This experience indicates that travel demand may have a high probability to change in the future and could be the main source of uncertainties for HSR design. Besides travel demand, functional requirement, like reliability and energy conversion may also change in the future. For example, the customers may require an HSR system with a higher reliability rate in the future, or the government agency requires the HSR system with a higher energy conversion rate. The change of theses functional requirements will significantly affect the lifecycle performance of the HSR system. Therefore, these functional requirements are also the source of uncertainties.

Except these five key features, others are treated as constant in the case study. This assumption is valid for the HSR design problem. Take the functional requirement of safety for example. In the initial design phase, one important design objective is to achieve 100% safety in its operational phase. Moreover, this high requirement of safety design will not change in the future operation process. Therefore, the functional requirement of safety is an important feature of the HSR system but is not a source of uncertainty.

<u>Subsystem-level design variables for key uncertainties</u>

Once the set of exogenous uncertainties is identified, the next step is to identify the design variables in subsystem-level. HSR system is viewed as a system made up of several components, including the station, the vehicle and the track. The subsystems for each component are identified according to Chou and Kim (2009), Chang et al., (2000), Campos and De Rus (2009), Whitford and Karlaftis (2003). The design variables in subsystem-level are shown in Table 6.2.

Table 6.2 Design variables in HSR system

Components	Subsystems
Station system	Span of service, waiting space on station, number of stations, frequency, arrangement of moving rout, in-station facilities, dwell time at each station
Vehicle system	Configuration of the train, seating capacity, accelerate system, brake system, control system, track-train interactions, personal space on train, traction system, operating speed, gearing system, total weight, communication system, aerodynamic system, propulsion system
Track system	Design speed, signaling system, curvature, catenary, gradient design, superelevation of the track

<u>Complex relationship identification</u>

Mapping the influence relationships between the uncertainty space to the design variable space, as well as identifying complex interconnections among design variable are critical steps in this case study. These tasks are based on technical background and design knowledge, which is extracted from existing research papers or experienced experts. In this case study, we learned the technical knowledge based on expert communications and publicly available information, such as Hay (1982),Whitford and Karlaftis (2003) and

Wright and Ashford (1989). Here, we take the exogenous factor—actual travel time for example. Several design variables are related to the actual travel time: 1) train's ability to negotiate curves; 2) train's ability to accelerate and decelerate quickly; 3) number of stations and dwell time at each station. Specifically, if passengers require shorter travel time, the related design variables (e.g. accelerate system, brake system, dwell time and number of stations) are needed to change.

The mapping relationships from exogenous uncertainties to design variables as well as the interconnections among design variables are identified systematically. The influence relationships are represented using a directed graph and DSM representation, as shown in Fig 6.2 and Fig 6.3.

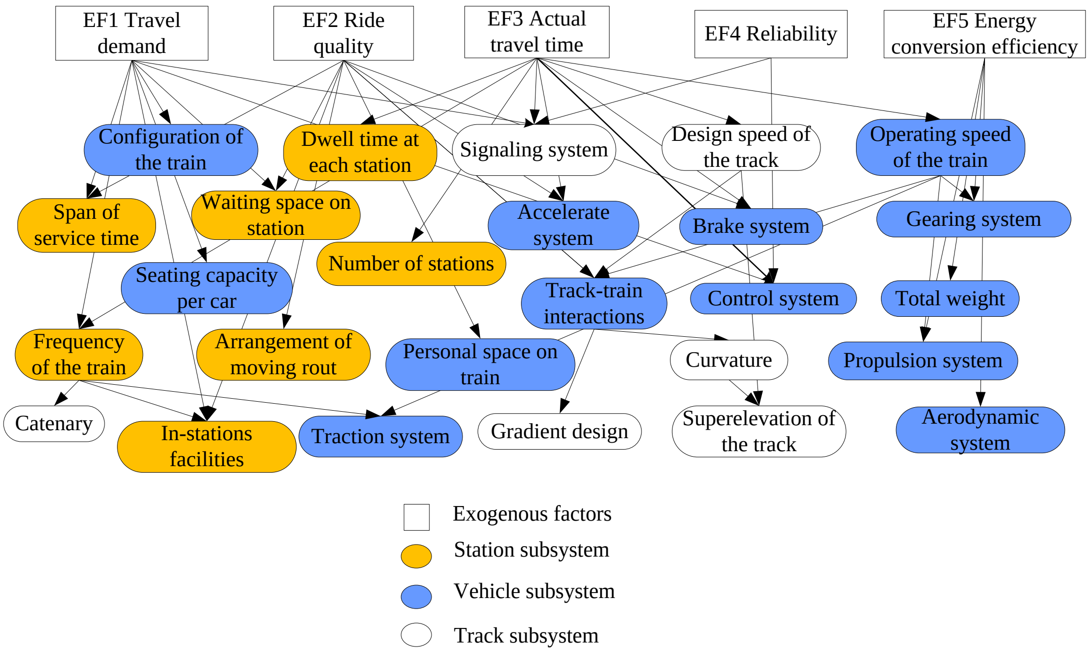


Fig 6.2 The directed graph of HSR system

			External Factors					Subsystem-level Design Variables																									
								Station Component									Vehicle Component																
			ef_1	ef_2	ef_3	ef_4	ef_5	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	x_{20}	x_{21}	x_{22}	x_{23}	x_{24}	x_{25}	x_{26}
Subsystem-level Design Variables	Station	x_1 Dwell time			1																												
		x_2 Waiting space	1	1																													
		x_3 service time	1	1																													
		x_4 Stations Number			1																												
		x_5 Frequency	1		1																												
		x_6 Moving route		1																													
		x_7 Facilities	1	1								1																					
		x_8 Configuration	1																														
	Vehicle	x_9 Seat capacity	1																														
		x_{10} speed			1																												
		x_{11} Accelerate		1	1																												
		x_{12} Brake system		1	1																												
		x_{13} Gearing					1										1																
		x_{14} Interactions		1													1												1				
		x_{15} Control	1		1	1																											
		x_{16} Total weight					1																										
		x_{17} Space		1																													
		x_{18} Traction										1					1																
		x_{19} Aerodynamic					1																										
		x_{20} Propulsion					1										1																
		x_{21} Signaling	1		1	1																											
	Track	x_{22} Speed of track			1																												
		x_{23} Curvature																			1												
		x_{24} Catenary										1																					
		x_{25} Gradient design																			1												
		x_{26} Superelevation																											1	1			

Fig 6.3 The DSM representation of HSR system

6.3.2 Flexible Design Opportunity Selection

In this case study, there are 26 design variables and 5 exogenous uncertainties. Using the sensitivity-based method, 10 design variables have sensitivity value 1, 13 design variables have sensitivity value 2, and 3 design variables have sensitivity value 3. It is found that the design variable of "in-station facilities", "signaling system" as well as "control system" are the most sensitive variables in this case. It is influenced by travel demand, ride quality, actual travel time and reliability respectively. Therefore, the HSR system will be more nimble in the future when the variable of "in-station facilities", "signaling system" and "control system" are designed with flexibility. Next, we will add flexibility into the "in-station facilities" and compare the flexible system design with the inflexible design by discussing the anticipated performance—net present value of total costs.

6.4 Economic Evaluation

After identifying the variable for embedding flexibility, the system designer needs to generate flexible design concpets. Based on the analysis above, we analyze the “in-station facilities” design variable. Specifically, we focus on the development of a pedestrian bridge in a station. The pedestrian bridge is built to transfer passengers to access the platforms. The numbers of bridges depend on travel demand in the region and ride quality for passengers. If fewer bridges are developed, the bridges may become too crowded when travel demand increases quickly. And passengers’ satisfaction may decrease. A cost of failing to meet the service quality should be considered (C_{cof}). On the other hand, if more bridges are developed, more maintenance cost is needed. Therefore, the problem here is how to design the pedestrian bridges in order to minimize total cost.

In this case study, possible performances of design strategies are assessed under travel demand uncertainty. The following assumptions are made for the economic evaluation:

- The time horizon is 20 years.
- We assume that the deterministic forecast of travel demand in the first year is 7.5 million. A Geometric Brownian Motion (GBM) model is chosen for modeling future demand prediction. The reasons for choosing GBM process are as follows: 1) travel demand of transportation system usually increases continuously with some

unexpected shocks and the GBM model is suitable to model the dynamics of demand; 2) the GBM model has been widely used to represent future demand in the capacity studies in existing research. For example, Marathe and Ryan (2005) and Pereira et al., (2006) modeled airline demand, Pimentel et al., (2012) modeled the demand for a new HSR system, and Rose (1998) modeled highway traffic. The existing work shows that modeling travel demand follows as GBM process is a reasonable assumption. The parameters and their assumed values for this GBM model are shown in Table 6.3. Fig 6.4 shows five simulations for the evolutions of travel demand based on the GMB model.

Table 6.3 Parameters for travel demand uncertainty model

Parameters	Values
Drift rate u	4% per year
Volatility σ	10%
Simulation interval Δt	1 year

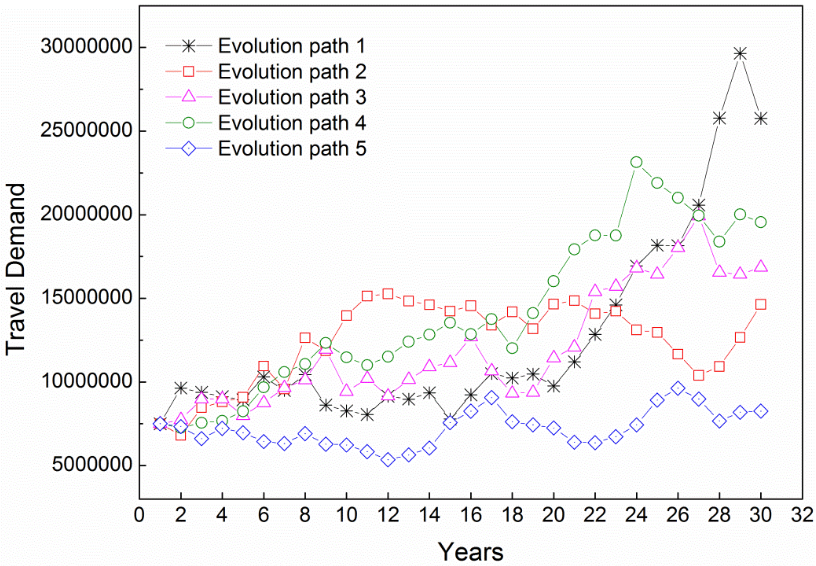


Fig 6.4 Evolutions of travel demand based on the GMB model (5 trajectories)

- The design capacity of pedestrian bridge is assumed to be 5000 people per hour. The flow volume of bridge in the off-hour could be calculated using Eq. (6.1):

$$FV_t^{off-hour} = TD_t/(OD_t \times OH_t) \tag{6.1}$$

where TD_t is the prediction travel demand at year t; OD_t is the operating days at year t; OH_t is the average operating hours per day at year t (e.g. OD_t=365 and OH_t=12). The flow volume of peak-hour is 2.5 times the flow volume of off-hour.

- The flow volume during peak-hour should not exceed a certain level of capacity. This certain level of capacity should less than the design capacity (e.g. 4000 people per hour). If flow volume at peak-hour exceeds the certain level of capacity, the travelers may feel too crowded in the station. A cost of failing to meet the service quality will be charged. This cost (C_{cof}) will increase 20% for every year.

6.4.1 Design Strategies Generation

Based on the above information, three design concepts are compared in this case study:

Strategy A: one big design

This design estimates a best capacity in the initial design phase with no change in the future. In this strategy, two pedestrian bridges are built on the station. This strategy gains benefits due to economies of scale (EOS). However, this strategy might lead to oversized capacity if the travel demand turns out to be less than expected. In addition, the design could also be undersized. And cost of filling to meet the service quality C_{cof} is needed when travel demand exceeds the expected capacity.

Strategy B: simple extension design

This strategy develops one bridge in the initial phase. The additional bridge could be built with high extension/switching cost (i.e. $C_{S-switch}$), once the travel demand exceeds design capacity in two consecutive years. Compared to one big design, it is a flexible design based on future travel demand. It leads to less exposure to the risk. However, there are two disadvantages of this strategy: 1) as the extension/switching cost for additional bridge is very high, the total costs for the long lifecycle may increase if travel demand turns out to be very high, 2) loses the economies of scale for initial development.

Strategy C: flexible extension design

Like simple extension design, the number of bridge and timing of extension are all flexible in the flexible extension design. The difference is that the designers can design flexible option in the initial development phase, to build an additional bridge easily in future. A premium is required to acquire the flexible option. This premium is called as the cost of option (C_{opt}). It assumes that the cost of option is 10% of the development cost in simple extension design. Therefore, the initial development cost for flexible extension design is more than that of simple extension strategy. However, the option has a benefit that lower switching cost (i.e. $C_{F-switch}$) is required in the future. It is 70% of the switching cost in simple extension design ($C_{S-switch}$).

The assumed development cost and maintenance cost are summarized in Table 6.4. All costs are normalized to the initial development cost of simple extension design.

Table 6.4 The assumed construction and maintenance cost per year

	Strategy A	Strategy B	Strategy C
Initial development cost (per bridge)	90,000	100,000	110,000
Annual maintenance cost (per bridge)	1000	1000	1000
Cost of failing (in the first year)	4000	0	0
Cost of option	0	0	10,000
Switching cost (per bridge)	0	100,000	70,000

6.4.2 Economic Model Development

The total cost of each design strategy can be calculated as follows:

$$NPV_i = \sum_{0}^{T} \frac{TC_i^t}{(1+r)^t}$$

where $$TC_i^t = C_{initial_i} + C_{maintain_i} N_i^t + C_{cof_i}^t + C_{switch_i}^t \quad (6.2)$$

NPV_i is the net present value of total cost for strategy i, $i \in A, B, C$; TC_i^t is the total cost for strategy i at year t; $C_{initial_i}$ is the initial development cost for strategy i ; $C_{maintain_i}^t$ is the annual maintenance cost for strategy i at year t; $C_{switch_i}^t$ is the switching cost for strategy i at year t; $C_{cof_i}^t$ is the cost of failing to meet service quality for strategy i at year t; N_i^t is the number of bridges developed for strategy i at year t. The initial development cost for strategy i is calculated using the following equation:

$$C_{initial_i} = C_{F-initial_i} + C_{opt_i} \quad (6.3)$$

Where $C_{F-initial_i}$ is the fixed initial development cost for strategy i and C_{opt_i} is the additional cost required to enable flexibility.

When actual travel demand in peak-hour exceeds a certain level of capacity in three consecutive years, $C_{cof_i}^{t}$ is needed (equals to 4000 in the first year). It will be increased very year with a rate α (α is 20% in this case). This type of cost is only in the one big strategy. It will equal to zero in other strategies since extension will occur in the future. The cost of failing to meet the requirement can be calculated by Eq. (6.4):

$$C_{cof_A}^{t} = C_{cof_A}^{t-1}(1+\alpha) \tag{6.4}$$

The anticipated performance of this case study is the net present value of total costs. It should be noted that the discount rate for calculating the net present value of total cost is assumed to be 8%.

6.5 Strategies Comparison

6.5.1 Simulation Results and Discussions

Monte Carlo Simulation is used to generate 3000 travel demands for each strategy. The corresponding total cost is calculated according to Eqs. (6.2) - (6.4). The cumulative distributions of net present value of total costs for three strategies are compared in Fig 6.5. Table 6.5 summarizes the key statistics of the economic metrics for each strategy.

Table 6.5 Summary of economic statistics for the three strategies

Development strategies	Total Cost		
	Expected Value	Minimal Value	Maximal Value
One big design	204,428	199,636	307,357
Simple extension design	184,840	109,818	319,984
Flexible extension design	176,482	119,818	298,382

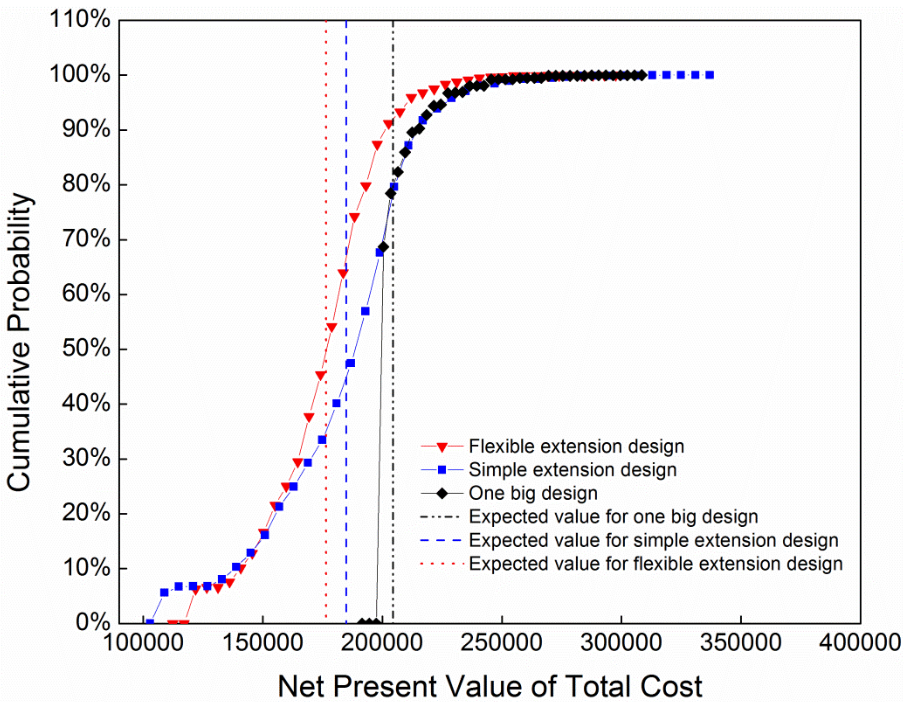


Fig 6.5 Cumulative distribution of net present value of total cost

Based on the comparisons of net present value of total costs in Fig 6.5 and Table 6.5, we find that the flexible extension design outperforms other strategies. The flexible extension design has the smallest expected total cost (176,482) in this case. The value of flexibility for flexible extension design is 27,946. It suggests that flexible extension design could have 13.6% improvement over one big strategy as well as 4.5% improvement over simple extension strategy. However, the minimal total cost of simple extension strategy (109,818) is less than that of flexible extension strategy (119,818).

The data show that the simple extension strategy has better performance than flexible extension strategy when the travel demand does not significantly increase. One possible explanation is that when the uncertainty of travel demand does not significantly increase, one bridge is enough to service future travel demand. Therefore, it is not worth for the extra investment of flexibility.

To illustrate the overall system performance and discuss the accuracy of the results, a further hypothesis testing is conducted. The null hypothesis H_0 here is defined as the expected total cost of flexible extension design (EC_{fle}) is larger than or equal to that of the one simple design (EC_{fix}), while the alternative hypothesis $H_A$is defined as $EC_{fle} < EC_{fix}$. A standand one-tail z-test (two samples for mean) is conducted to compare the expected value of the two samples (3000 times simulation for each sample). The result of the z-test with 99% significance level yields z=-56.28 (p<0.01). The data is strongly suggestive that null hypothesis is rejected.

A same z-test is also conducted between the sample of the flexible extension design and the sample of the simple extension design, using the same number of simulation replication (i.e. 3000 simulations). The result of the z-test yields z=-11.21 (p<0.01). This result indicates that the expected cost of flexible extension design is less than that of the simple extension design with 99% confidence. The discussion here also shows that 3000 simulations for each sample could guarantee the accuracy of the results with 99% confidence level.

6.5.2 Sensitivity Analysis

The simulation results depend on the assumptions in uncertainty model and economic model. In this section, the sensitivity of the assumed parameters, such as the cost of options and the benefit of options are studied. The goal of this sensitivity analysis is to discuss the results when assumed parameters are changed. It should be noted that the sensitivity here is different from that in Chapter 4. Here, sensitivity means modifying the parameters from the nominal values over a wide range to identify the effect and the change of results.

We assume that the cost of option in the flexible extension design is 10% of the development cost in the simple extension design. Table 6.6 shows the sensitivity of the cost of options. It is expressed as a percentage of the development cost.

Table 6.6 Sensitivity analysis of cost of option for the flexible extension strategy

Cost of option	5%	10%	20%	30%	40%
Expected Value	171,856	176,975	186,488	196,727	206,670

From Table 6.6, we can see that the expected value of the total cost for the flexible extension design will increase with the increase of the cost of option. The expected total cost of flexible extension design is still lower than that of simple extension design (184,840) when the cost of the option is 10%, but slightly higher when it increases to 20%. The expected cost of flexible extension design is higher than both of designs when the cost of the option increases to 40%.

The benefit of option is a reduction of future switching cost due to flexible option. In this case, we assume the future switching cost in the flexible extension strategy is 70% of that in simple extension strategy. Table 6.7 shows the sensitivity analysis of benefit of options for flexible extension strategy. It shows that the expected total cost of flexible extension design will decrease 10.3% when the benefit of options changes from 95% to 60%. The expected cost of the flexible extension design remains lower than that of the one big design (204,428) when the benefit of options is up to 95%.

Table 6.7 Sensitivity analysis of benefit of options for flexible extension strategy

Benefit of option	95%	90%	85%	80%	75%	70%	65%	60%
Expected Value	190,234	188,380	185,088	183,337	178,882	176,651	173,532	170,697

The expected total cost of flexible extension design also changes when the rate of C_{cof} and the discount rate r are changed. To see this sensitivity, additional simulations are conducted. Table 6.8 shows the sensitivity analysis of the increase rate of C_{cof} for the flexible extension strategy. The results indicate that the decision for selecting the flexible design will not change when the increase rate change from 5%-40%.

Table 6.8 Sensitivity analysis of the increase rate of C_{cof} (α) for flexible extension strategy

Increase rate of C_{cof}	5%	10%	20%	30%	40%
Expected Value	174,192	175,669	176,836	177,974	182,236

The expected total cost for the flexible extension design is estimated when the discount rate range from 6% to 20%, with a 2% step. Table 6.9

summarizes the sensitivity analysis results. It shows that the expected total cost decreases when the interest rate increases. The flexible extension design performs better than the fixed design when the interest rate within the range from 6%-20%.

Table 6.9 Sensitivity analysis of interest rate (r) for flexible extension strategy

Interest rate	6%	8%	10%	12%	14%	16%	18%	20%
Expected Value	187,048	176,766	167,927	162,135	156,595	152,528	148,392	145,535

6.6 Summary

This chapter evaluates sensitivity-based method through a case study of a HSR system. The exogenous uncertainties, subsystem-level design variables as well as complex influence relationships of the HSR system are analyzed. The “in-station facilities”, “signaling system” and “control system” are the most sensitive design variables, which are selected by sensitivity-based method. In this case, we focus on the design of a pedestrian bridge for “in-station facilities”. Three development strategies of pedestrian bridge, namely one big design, simple extension design and flexible extension design, are modeled and simulated under travel demand. The results show that the flexible extension design is better, since it has 13.6% and 4.5% improvement over the rest two strategies respectively. This provides clear evidence that adding flexibility in the selected opportunity could improve system performance in long term perspective. By conducting sensitivity analysis of parametric assumptions (e.g. the cost of option and the benefit of option), we find that the flexible extension design remains superior to others over certain ranges of parametric values.

Chapter 7 Case Study 2: Flexible Design for Railway Signal System

7.1 Introduction

The purpose of this case study is to evaluate the risk susceptibility method, within the application domain of the HSR system. Different from the case study in Chapter 6 which emphasizes on the whole HSR system, this case study aims to identify the flexible design opportunities for a specific subsystem: the railway signal system. Here, the railway signal system includes signal component, communication component and control component. The case study in this chapter analyzes the flexible design concepts on a parameter-level. The flexible design strategies which are selected by the risk susceptibility method will be compared with an inflexible design strategy, as well as a flexible design strategy identified by sensitivity-based method. The anticipated performance of each design strategy will be measured. The following section 7.2 introduces the background information of the railway signal system. Section 7.3 describes the flexible design procedures using risk susceptibility method. Section 7.4 develops design strategies and makes assumptions. Section 7.5 compares the different design strategies and discusses the results. Section 7.6 summarizes the overall results of this case study.

7.2 Railway Signal System Overview

The railway signal system is fundamental to the safe, efficient operation of the HSR system. Since signals control the movement of high speed trains, signal system plays an important role in the operation process of high speed lines. It not only determines maximum speed and capacity to operate efficiently, but also provides safety and reliability. In general, railway signal systems provide the following two functions (Ullman and Bing 1994, Nash 2003):

- Block signal: prevent trains from colliding on the same track. On high-speed lines, block signal systems are operated by some support components, such as cab signaling.
- Interlocking signal: prevent trains from colliding when changing tracks.

In order to provide good service of block signal and interlocking signal, communication and control components are supported for the high speed line. The communication component uses the communication network to share signal and information between control component and trains, while the control component remotely controls all the interlocking points and manually controlled points to make the trains run safely on tracks in both directions. Fig 7.1 shows basic signal functions and the relationships among components. The complex relationships within the railway signal system are investigated and analyzed in section 7.3.1.

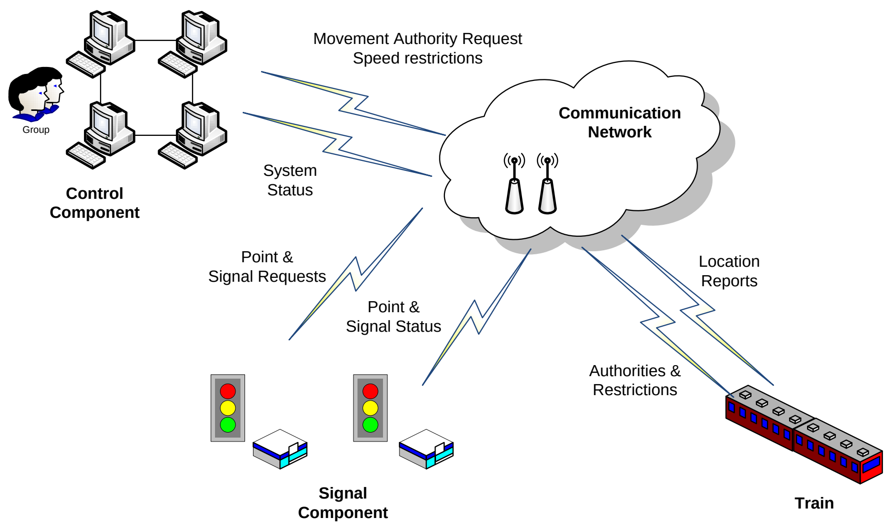


Fig 7.1 Railway signal system

7.3 Design Procedure for Flexibility

7.3.1 Initial Analysis of Railway Signal System

The initial analysis of risk susceptibility method includes exogenous uncertainty analysis and internal connection analysis.

Exogenous uncertainty analysis

Many exogenous uncertainties for HSR system are analyzed in Chapter 6. As it is shown in Fig 6.3, five key exogenous uncertainties are selected in the analysis process. In this case study, we just focus on the mapping relationships with regard to the railway signal system. Specifically, we just analyze how the exogenous uncertainty: travel demand, reliability and actual travel time affect the signal system in a parameter-level design.

Analyzing design features is the best way to map exogenous uncertainties to parameter-level design variables. As for dealing with exogenous uncertainty of travel demand, the operators could change the service time, change the train’s configuration, or change the capacity from the perspective of the whole HSR system. However, from the perspective of the signal system, the service time and train's configuration cannot control by the signal system. Only the future of capacity is related to adapting new travel demand of the HSR system. The capacity here is defined as the number of trains that can be operated over a given section of railway track per unit of time (e.g. 20 trains per hour). As travel demand turns to be upside, so need to increase design capacity, and thus triggers the change of related design variables within signal system (e.g. block length and system aspects of signal system).

Similar as travel demand, many design features relate to the exogenous uncertainty of actual travel time when we analyze the whole HSR system, such as accelerate ability, distance between stations as well as maximum design speed. However, only one design feature--maximum design speed is related to the design of signal system. For example, the change of maximum speed may trigger the change of braking distance design and speed control design within a signal system. As for the exogenous uncertainty of reliability, it is the ratio between the number of on time arrival train and total arrival train. The signal component and control component are all related to this uncertainty.

In this case study, a set of exogenous uncertainty factors for signal system ef_{ss} is defined as:

$$ef_{ss} = [C(t), S(t), R(t)] \tag{7.1}$$

$C(t)$ is the track capacity of the high speed railway system as a function of time t, $S(t)$ is the maximum design speed of trains as a function of time t, and $R(t)$ is the reliability requirement of high speed railway system as a function of time t. In this case study, the design features which are discussed above are used to represent the exogenous uncertainties, since they can easily establish the mapping relationship between the external environment and parameter-level design variable. It should be noted that although safety is the most important aspect of railway operation and is highly impacted by signal system, it is not a source of exogenous uncertainty in this case study. This is because the HSR system is designed to achieve a very high level of safety in the initial phase. And this high requirement of safety design will not change in the future. Therefore, the functional requirement of safety is not a source of uncertainty for HSR system.

Internal connection analysis

Once the set of exogenous factors ef_{ss} is identified, the next step is to establish the mapping relationship from exogenous uncertainties to parameter-level design variables, as well as investigate the complex interconnected relationship among design variables. These interconnections of signal system are analyzed within signal component, communication component and control component respectively.

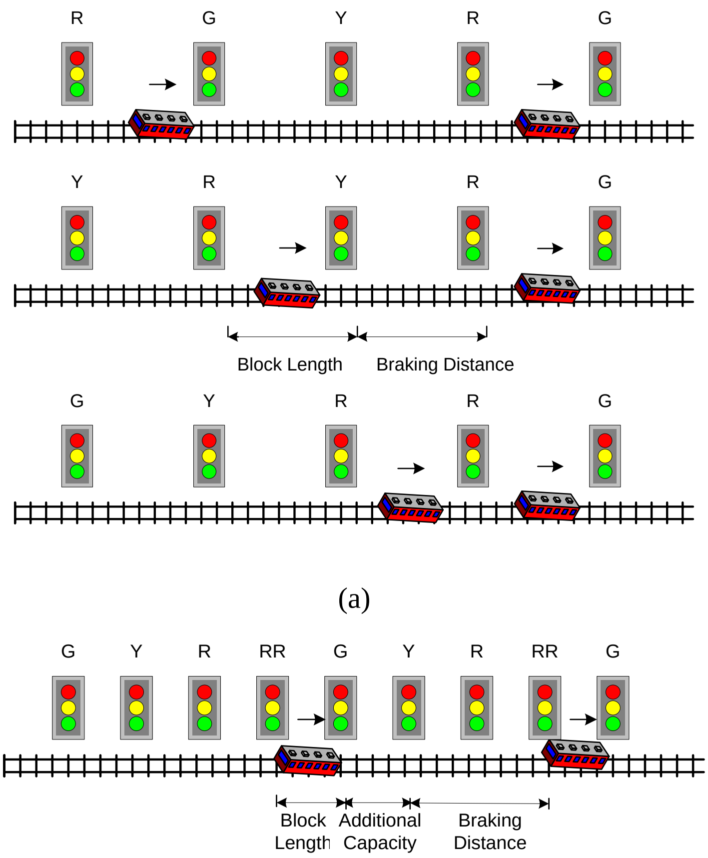
As discussed previously, the signal component provides two basic functions—block signal and interlocking signal. The block signal system is designed to tell trains to stop when there is a danger of colliding on the same track. Since trains take a long distance to stop, the train operator must know well in advance. Therefore, block signal systems are designed around braking distance. According to Nash (2003), the braking distance of train is based on train characteristic (i.e. speed, braking ability, and weight) and track condition (i.e. gradient, weather, and curvature). As the exogenous uncertainty of maximum speed increase, the braking distance may increase.

Another important design variable is the block length (distance between signals), which is designed based on the braking distance. It must be long enough to enable the train with the longest braking distance operating on the track to stop. Therefore, as speed increases, so do braking distance, and thus block length. Besides the relationship with exogenous uncertainty of maximum speed, the block length also plays an important role in determining a railway's capacity. The longer the block length, the lower the rail way's capacity, when the other design variables are equal (Nash 2003).

The number of aspects is also a critical design variable in the block signal system. The simplest automatic block signal (ABS) system is based on three aspects: stop, approach, and clear. Since adding aspects to the block signal system provides finger control of train movement and reduces the excess train spacing, it is the simplest way to improve the railway capacity (Nash 2003). Table 7.1 summarizes the meaning of different aspects of the block signal system. It should be noted that R or RR signal depends on the number of blocks required to stop the train. Fig 7.2 shows the automatic block signal system with different aspects.

Table 7.1 Aspects of block signal system

Signal Color	Signal Name	Indication
G=Green	Clear	Proceed
Y=Yellow	Approach	Stop at next Signal
R=Red	Stop	Stop
RR=Double Red	Stop	Stop



(b)

Fig 7.2 (a) Three-aspect ABS system, (b) Four-aspect ABS system (The technical knowledge is from Nash (2003) and Ullman and Bing (1994))

Interlocking signal is the second basic function of the signal component. It enables a train to change from one track to another, or divert from the main track to a siding (by throwing a switch) and prevent other trains from conflicting with the train in siding tracks (by signal change). Generally, a controller sets up a route for a train through a series of switches, and the interlocking is remotely controlled to prohibit conflicting train movement (Ullman and Bing 1994). Using the interlocking system effectively can improve the performance of the HSR system (e.g. increase reliability and capacity of HSR system).

In terms of the signal control system, we analyze the interconnection from two major sub-components. First, all the interlocking and controlled points are remotely controlled from a central location, called centralized traffic control (CTC). It uses the block signal and interlocking signal to control train movements. Since CTC enables dispatchers to route trains through the network and provides instructions to train operators, clear priority design and computerized dispatching assistance design can increase the reliability and capacity of the HRS system. For example, if high speed trains always have first priority, the dispatcher could instruct the regular train to wait until the high speed train passed it first. This would reduce delay to the high speed train, however, it may increase delay for other trains and finally impact the overall reliability rate. The second sub-component is related to the control design on the train. Automatic cab signaling (ACS) is one of the designs, which receives information from CTC and provides control information to train operators by displaying signal information on the operator's control panel (Ullman and Bing 1994). The ACS can be designed with two types: intermittent type which displays the last signal information until the train passes the next signal, as well as continuous type which displays the signal information in real time. Different from ACS, train speed control (TSC) takes control of the train if the operator does not take appropriate actions after receiving signal information. The simplest type of TSC is the automatic train stop which stops the train automatically when there is danger. A high level of TSC is the automatic train control which not only stops a train but also controls its speed. The different external environment and requirement may change the type of ACS and TSC.

Similar to signal control system, the signal communication system also comprises two major sub-components: terminal cabinets which serve as junctions in the communication system, as well as interconnects which run overhead or through underground conduits. Although the signal communication system is a vital link between signal component and control component, we assume that it may not trigger a change within a signal system, since it serves as a support component to the railway signal system.

Fig 7.3 summarizes the key exogenous uncertainties and design variables of the railway signal system. The notions ef_1, ef_2 and ef_3 in the matrix are maximum design speed, design capacity and reliability. For simplification, the triggering probabilities in this case are classified and represented into three levels. The numbers in Fig 7.3 represent the likelihood and dependent relationships. The higher the number showed in the ESM cells, the stronger relations exist between the system elements. An empty cell shows no explicit change relation expected between the two system elements. The values assigned to the triggering probability in this thesis are not arbitrary, since the complex relationships are analyzed based on the technical reports and existing papers (e.g. Government Accountability Office 2010, Quandel Consultants 2011).

It should be noted that numbers here indicate the influence relationship rather than information flow. For instance, change design variable s_9 terminal cabinets cannot trigger the change of design variable s_7 interlocking. Thus, no number exists in the corresponding slot, although information flow exists from s_9 terminal cabinets to s_7 interlocking.

		External Factors			parameter-level Design Variables																
					Trains Factors			Signal Component					Communication & Control								
		ef_1	ef_2	ef_3	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8	s_9	s_{10}	s_{11}	s_{12}	s_{13}	s_{14}	s_{15}	s_{16}	s_{17}
parameter-level Design Variables — Trains Factors	s_1 Brake ability	0.3																			
	s_2 Curvature	0.3																			
	s_3 Gradient	0.3																			
Signal Component	s_4 Braking distance	0.9			0.9	0.9	0.9														
	s_5 Block length		0.9					0.6													
	s_6 System aspects		0.9																		
	s_7 Interlocking		0.6	0.6																0.6	
	s_8 Switches																				
Communication & Control	s_9 Terminal cabinets																				
	s_{10} Interconnect																				
	s_{11} Control point																				
	s_{12} Cab signaling	0.9																		0.6	
	s_{13} Speed control signaling	0.9														0.3					
	s_{14} Dispatching assistance			0.9																	
	s_{15} Priority design			0.9																	
	s_{16} Centralized traffic control	0.3	0.9								0.3					0.3	0.3	0.6	0.6		
	s_{17} Control type																				

Fig 7.3 ESM representation with triggering probability of railway signal system

7.3.2 Build Bayesian Network Model

The preliminary model of railway signal system, which is built according to the data in ESM representation, is shown in Fig 7.4. It intuitively indicates influence relationships by a directed graph. Different from the ESM representation showed in Fig 7.3, some design variables were removed in the preliminary model (e.g. s_8 switches and s_9 terminal cabinets), since these design variables do not receive change propagation from exogenous uncertainties as well as other design variables. It should be noted that the preliminary model preserves all the direct influence relationships of ESM representation.

Fig 7.5 is a screenshot of the Netica tool[1] showing the Bayesian network model of the railway signal system. Visualization of the Bayesian network includes the name for each node and the state name of each node.

[1] Interested readers may consult Netica's website for further information: http://www.norsys.com/

Here, each node has only two states. State C means that a characteristic of system element has to change, while state S means the characteristic stays within a range and may not impact other system elements. For example, state C for *design speed* means that the design speed is required to achieve at a threshold value and may trigger the change of other system element. On the hand, state S means the design speed to stay within a range. The dependencies between nodes are shown as edges and the combined probabilities are shown as percentages.

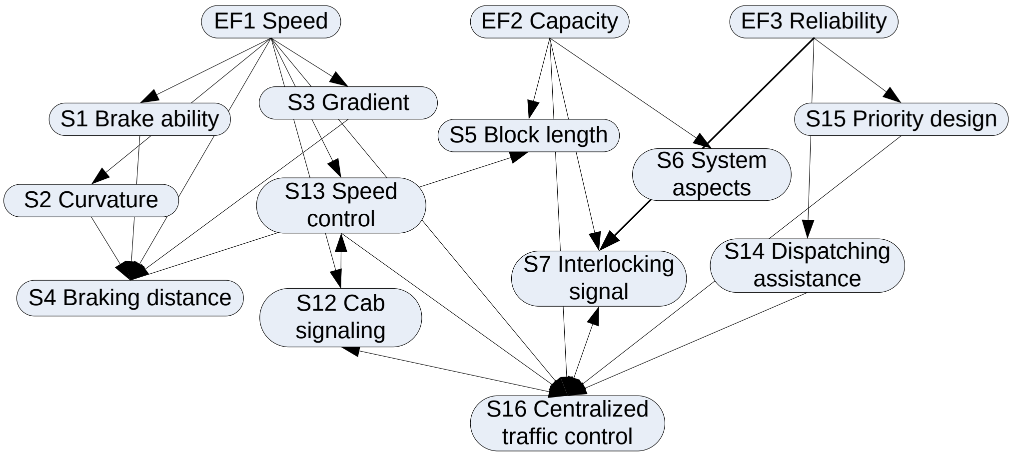


Fig 7.4 The preliminary model of railway signal system

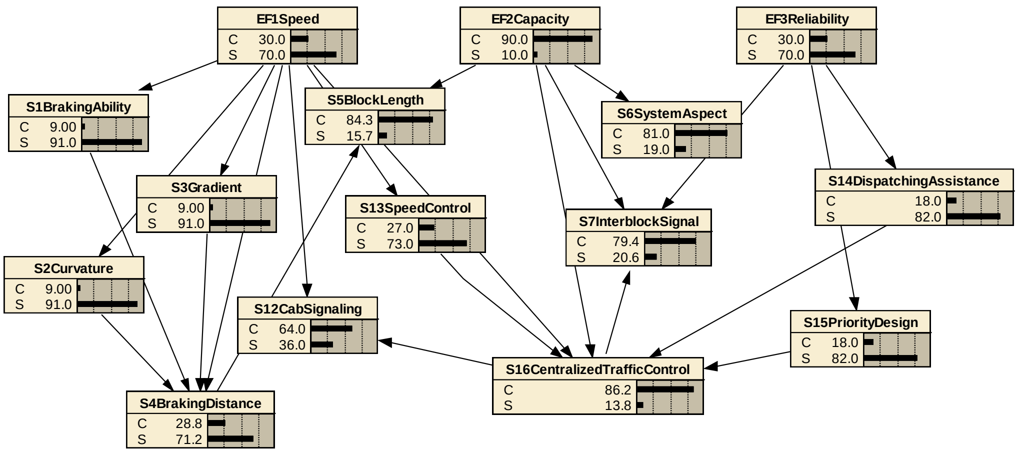


Fig 7.5 The Bayesian network model without evidence

7.3.3 Calculate Risk Susceptibility Index

As discussed previously, risk susceptibility index measures the risk of change propagation. It is presented by combined *conditional probability* and *switching costs*. As for the combined conditional probability, it can be easily derived from the Bayesian network by predictive reasoning function. For example, setting the values of exogenous uncertainties means that change takes place in the system. These changes are then propagated through the network, producing a new probability distribution over the remaining variables in the network (Korb and Nicholson 2004). The Bayesian network shows the what-if scenarios of the impact of change.

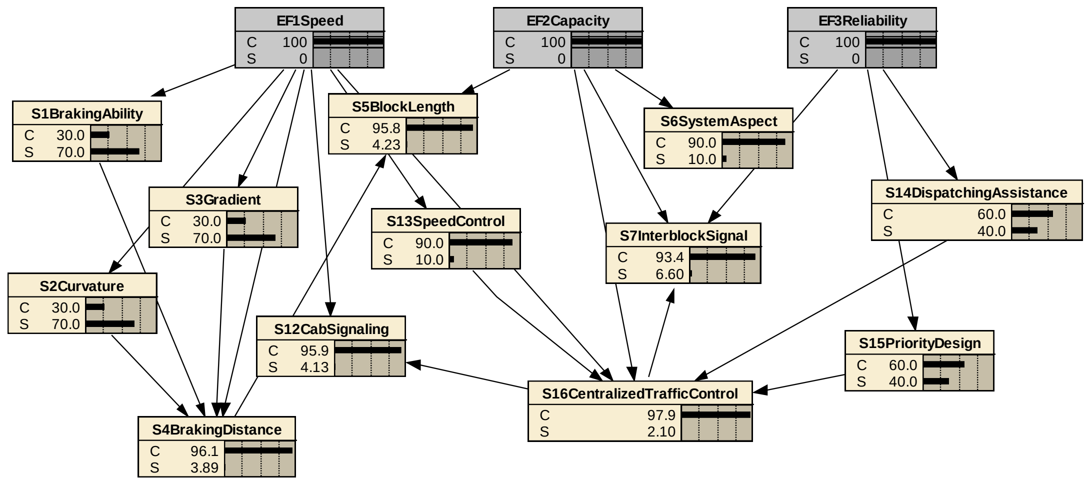


Fig 7.6 The Bayesian network model with evidence

Fig 7.6 shows an example of Bayesian network model with evidence. It assumes that all the exogenous uncertainties of the railway signal system are changed. These changes are inserted as evidence to set the change states of ef_1, ef_2 and ef_3 to be 100% (see the highlighted node in Fig 7.6). Given this evidence, we can do a what-if analysis and predict that design variable s_{16} will be changed with a probability of 97.9%. Other combined triggering probabilities are summarized in Table 7.2.

Table 7.2 Combined conditional probability for four scenarios

BN node	Scenario 1 P(ef_1=C)=100% P(ef_2=C)=100% P(ef_3=C)=100%	Scenario 2 P(ef_1=C)=100% P(ef_2=C)=100% P(ef_3=C)=0	Secenario3 P(ef_1=C)=0 P(ef_2=C)=100% P(ef_3=C)=100%	Scenario 4 P(ef_1=C)=0 P(ef_2=C)=100% P(ef_3=C)=0
s_1	30	30	0	0
s_2	30	30	0	0
s_3	30	30	0	0
s_4	96.1	96.1	0	0
s_5	95.8	95.8	90	90
s_6	90	90	90	90
s_7	93.4	82.8	93.2	81.6
s_{12}	95.9	95.7	57.5	54
s_{13}	90	90	0	0
s_{14}	60	0	60	0
s_{15}	60	0	60	0
s_{16}	97.9	94.9	95.9	90

Table 7.2 summarizes all the combined conditional probabilities for the four scenarios: 1) the three functional requirements: design speed, capacity and reliability are changed simultaneously, 2) the functional requirement of design speed and capacity are changed, 3) the functional requirement of capacity and reliability are changed, 4) only the functional requirement of capacity is changed. The three highest combined conditional probabilities for each scenario are observed (grayed cell). We can find that design variables s_5 and s_{16} are highlighted three times in four scenarios. This implies that design variables s_5 and s_{16} has high probabilities to change in these four scenarios. It should be noted that the combined conditional probability of s_6 keeps as a constant in the four scenarios. This is because that the design variable s_6 is only impacted by ef_2 which do not change in these four scenarios.

Table 7.3 List of assumptions for initial cost and switching cost (×1000)

Design variables	Unit	Initial cost ($/unit)	Switching cost ($/unit)	Quantity	Total switching Cost ($)	Source/Comment
s_1 Braking ability	Each	3333	667	1	667	Braking ability design is a part of vehicle design. According to Zhang (2008), the total cost of each vehicle is $50 million from Germany's Siemens. The initial cost of braking ability design is assumed to be 1/15 of total vehicle cost.
s_2 Curvature	Mile	444	88.8	200	17760	The switching cost of curvature and gradient design is directly taken from Quandel Consultants (2011). It is assumed that appropriate tie renewal has taken place before the curves are adjusted.
s_3 Gradient	Mile	66	13.2	200	2640	
s_4 Braking distance	-	113	22.6	500	11300	The design of braking distance, block length and system aspects could be changed by installing or replacing wayside signaling. Design wayside signaling is part of CTC design (Quandel Consultants 2011). The installation cost for CTC system is near $0.34 million per mile. Here, we assume that design wayside signaling is 1/3 of total cost.
s_5 Block length	-	113	22.6	500	11300	
s_6 System aspects	-	113	22.6	500	11300	
s_7 Interlocking signal	Each	1244	248.8	25	6220	Design of interlocking signal involves installing signal components which need to put combination of turnouts and crossovers into operation. It is the same as Quandel Consultants (2011). And based on Quandel Consultants (2011), the control point will be installed very 20 mile.
s_{12}Cab signaling	Each	3333	667	1	667	Cab signaling and speed control signaling are on-board train equipment. They are estimated once for each train. The initial cost of these two design variables is also assumed to be 1/15 of total vehicle cost.
s_{13} Speed control signaling	Each	3333	667	1	667	
s_{14} Dispatching assistance	Each	1000	200	1	200	The dispatching assistance design and priority design are parts of Electronic Train Management System (ETMS) design. Based on Tse (2008), the initial cost for ETMS is $ 3.7 million. The initial cost for these two variables is assumed $1million.
s_{15} Priority design	Each	1000	200	1	200	
s_{16} Centralized traffic control(CTC)	Mile	170	34	500	17000	According to Quandel Consultants (2011), installation cost for CTC system is near $0.34 million per mile. This installation cost includes all communications and central dispatch equipment, track circuitry and wayside signaling. However, the design variable CTC here is communications and central dispatch. Thus, we assume that it is 1/2 of $0.34 million per mile.

As for the switching costs of each design variable, they are assumed as 20% of their initial development cost. Further explanatory details are listed in Table 7.3. The costs in the table are quoted nominally. All the data and the assumptions are derived from Zhang (2008), Quandel Consultants (2011), Levinson et al., (1997), de Rus (2008), Harbuck (2009) and Tse (2008). It should be noted that this railway signal system is designed for high-speed line with 500 miles. Table 7.4 shows all switching costs, which are normalized to the switching cost of design variable s_2. The three highest switching costs are highlighted with grey cells.

Table 7.4 Normalized switching cost for design variables

Design variable	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_{12}	s_{13}	s_{14}	s_{15}	s_{16}
Normalized Switching cost	0.04	1	0.15	0.64	0.64	0.64	0.35	0.04	0.04	0.01	0.01	0.96

After identifying combined conditional probability and switching costs, the risk susceptibility index (RSI) can be calculated by Eqs. (5.2) and (5.4). The RSI value for each design variable is summarized in Table 7.5. The highest values for each scenario are highlighted. It shows that design variable s_{16} has the highest value in all the scenarios. This implies that it is the suitable opportunity to embed flexibility option based on risk susceptibility method. In the next section, we may evaluate this flexible design opportunity, and compare the performance with others.

Table 7.5 RSI value for each design variables

BN nodes	Scenario 1	Scenario 2	Scenario 3	Scenario 4
s_1 Braking ability	-0.0104	-0.0104	0	0
s_2 Curvature	0.2784	0.27834	0	0
s_3 Gradient	0.0230	0.0327	0	0
s_4 Braking distance	0.6102	0.6102	0	0
s_5 Block length	0.6095	0.6095	0.5726	0.5726
s_6 System aspects	0.5726	0.5726	0.5726	0.5726
s_7 Interlocking signal	0.3271	0.2900	0.3264	0.2858
s_{12}Cab signaling	0.0360	0.0359	0.0216	0.0203
s_{13} Speed control signaling	0.0328	0.0233	0	0
s_{14} Dispatching assistance	-0.0009	-0.0364	-0.0076	0
s_{15} Priority design	-0.0009	-0.0364	-0.0076	0
s_{16} Centralized traffic control(CTC)	0.9364	0.9004	0.9156	0.8508

7.4 Economic Evaluation under Multiple Uncertainties

7.4.1 Design Strategies Development

Four design strategies are evaluated and compared in this case study. They are inflexible design, flexible design in variable s_5, flexible design in variable s_{16} and flexible design in variabless_{12}. The inflexible strategy gains benefits with less initial development cost. However, the design variables in inflexible design are changed without flexible options, as exogenous factors are changed. This may lead to more total cost for long-term analysis when exogenous factors change frequently. This is because that the design variable needs to change to fit the new environment with more switching cost. The inflexible design can serve as a baseline strategy. Different from inflexible design, flexible designs in variable s_5, s_{16} and s_{12} may benefit from the low switching cost. However, a premium is required to acquire the flexible option. The four design strategies are evaluated and compared in the following scenarios: 1) exogenous uncertainty speed, capacity and reliability are changed simultaneously, 2) speed and capacity are changed simultaneously, 3) capacity and reliability are changed simultaneously, 4) only capacity is changed.

In the following section, we may discuss three questions. The first question is how much flexibility should embed in engineering system, as well as what is the relationship between the value of flexibility and uncertainty. The flexible design in s_{16} will be compared with inflexible design under different degree of uncertainty in four scenarios. Second, the design priority of design variables is evaluated. Based on risk susceptibility method, the design variable s_5 and design variable s_{16} are the most suitable flexible design opportunities. The design priority of these two design opportunities is that design variable s_{16} outperforms design variable s_5, based on the data from Table 7.5. This design priority is consistent with the results of sensitivity-based method, since design variable s_{16} may be influenced by three exogenous uncertainties while design variable s_5 only has two. In the following section, we should also evaluate this design priority. Third, the performance of risk susceptibility method and sensitivity-based method are evaluated.

7.4.2 Assumptions in Uncertainty Analysis

In order to perform uncertainty analysis to evaluate different design strategies, the following assumptions are made:

- The cost of the option is a premium for acquiring flexible option. It assumes that the cost of flexible option is 10% of the initial cost.
- The benefit of option is assumed to save 30% of the switching cost for each change. The initial cost and switching cost for flexible design is

calculated based on data from Table 7.3. They are summarized in Table 7.6.

- The time horizon is 20 years.
- The operating cost and maintenance cost for each design variables are assumed to be the same. The anticipated preference is net present value of the total cost, which considers the performance of initial investment and switching cost for long-term perspective.

Table 7.6 Initial cost and switching costs for the flexible design (×1000)

	Total initial cost for flexible design ($)	Total switching cost ($)
s_1 Braking ability	3666.3	466.62
s_2 Curvature	97680	12432
s_3 Gradient	14520	1848
s_4 Braking distance	62150	7910
s_5 Block length	62150	7910
s_6 System aspects	62150	7910
s_7 Interlocking signal	34210	4354
s_{12}Cab signaling	3666.3	466.62
s_{13} Speed control signaling	3666.3	466.62
s_{14} Dispatching assistance	1100	140
s_{15} Priority design	1100	140
s_{16} CTC	93500	11900

- The discounted cash flow method is used to measure and compare the performance of each design strategy, with an annual discount rate of 8%.

In this case study, the anticipate performance of design strategy is calculated from a cost perspective rather than a profit perspective. The net present value of the total costs is obtained by Eq. (7.1):

$$TC = \sum_{t=0}^{20} \frac{CF_t}{(1+r)^t} \tag{7.1}$$

Where

$$CF_t = C_{init}^t + C_{switch}^t \tag{7.2}$$

TC is the sum of time discounted cost over a period of 20 years; CF_t is the total cost at time t; r is the discount rate; C_{init}^t is the initial investment that occurs at time t; C_{switch}^t is the switching cost that occurs at time t.

7.5 Strategies Comparison

7.5.1 Results Discussion

Monte Carlo Simulation is used to generate 5000 trials for each scenario. The net present value of the total cost for each trail can be calculated according to Eq. (7.1). Table 7.7 summarizes the expected value of total costs for two design strategies: inflexible design and flexible design in s_{16}.

Table 7.7 The expected total costs of inflexible design and flexible design in s_{16}

Scenarios	Every 5 years		Every 3 years		Every year	
	Inflexible design	Flexible design in s_{16}	Inflexible design	Flexible design in s_{16}	Inflexible design	Flexible design in s_{16}
1	503,857	503,893	578,634	573,762	1,009,280	968,563
2	501,368	501,616	574,618	569,620	996,220	957,452
3	471,261	471,625	523,326	517,571	820,424	780,627
4	468,694	469,571	518,759	513,968	804,852	768,032

Fig 7.7 represents the results. The table and figure demonstrate the performance of these two design strategies in four scenarios. In addition, they show the results under different degrees of uncertainties (e.g. exogenous

uncertainties in different scenarios are changed every 1 year, every 3 years and every 5 years). We find that the expected value of total costs for flexible design in s_{16} is less than that of inflexible design, when the exogenous factors change frequently (see Fig 7.7 bottom). In contrast, the expected values of total cost for these two strategies are almost the same, when the degree of uncertainty is very low (see Fig 7.7 top). This result appears to confirm that the value of flexibility would increase as uncertainty increases. It may provide guidelines for designers to respond to exogenous uncertainty. In addition, we can also find that the expected value of total costs for flexible design in s_{16} is slightly higher than that of inflexible design when the degree of uncertainty is low. This data implies that flexible design does not fit in all conditions. The benefit of option may be wasted when its operational environment changes little. Table 7.8 summarizes the value of flexibility for flexible design ins_{16}. The negative values in the table mean the benefit of option is wasted and inflexible design performs better.

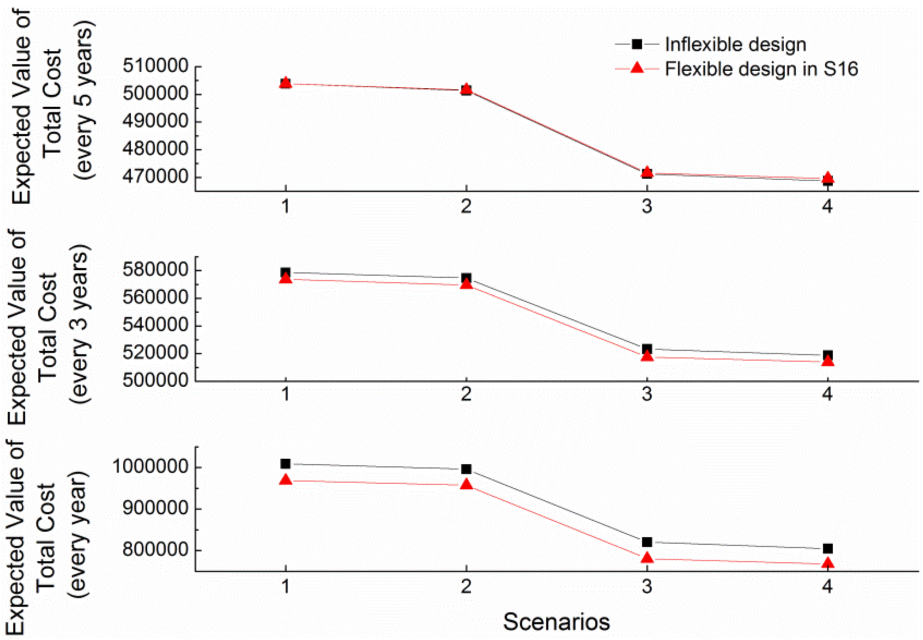


Fig 7.7 Comparison of expected value of total cost

Table 7.8 Value of flexibility for flexible design in s_{16}

Scenarios	Value of flexibility		
	Every 5 years	Every 3 years	Every year
1	-36	4,872	40,717
2	-248	4,998	38,768
3	-364	5,755	39,797
4	-877	4,791	36,820

The net present value of total cost for flexible design in s_5 and s_{16} are further calculated and compared. This experiment is conducted in scenario 3 with a high degree of uncertainty, in order to evaluate design priority. The cumulative distributions of total cost for these two strategies are shown in Fig 7.8. Table 7.9 summarizes the key statistics of the economic metrics for these two strategies. For comparison purpose, the economics metrics for inflexible design are also shown in this table.

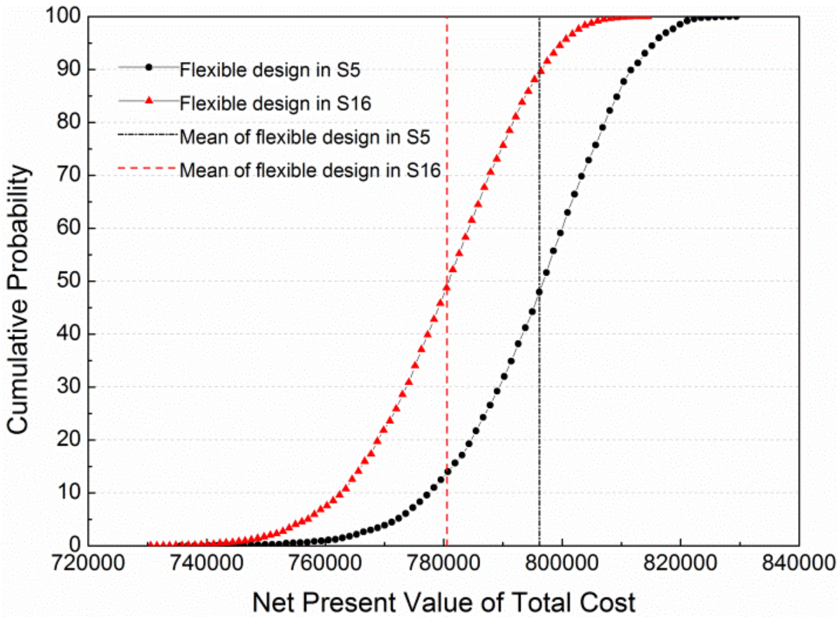


Fig 7.8 Cumulative distribution of total cost for flexible design in s_5 and s_{16}

Table 7.9 Summary of economic statistics of three strategies

Development strategies	Total Cost		
	Expected Value	Minimal Value	Maximal Value
Flexible design in s_5	795,943	738,087	827,305
Flexible design in s_{16}	780,881	724,588	813,467
Inflexible design	820,103	756,953	855,210

We find that the flexible design in s_{16} outperforms the flexible design in s_5, since it has less expected total cost than others. Specifically, the value of flexibility for flexible design in s_{16} is 39,222, while the value of flexibility for flexible design in s_5 is 24,159. The flexible design in s_{16} has 4.7% improvement over the inflexible design; while the flexible design in s_5 just has 2.9% improvement. This result confirms that the flexible design priority which is recommended by risk susceptibility method is reasonable. Fig 7.9 shows the frequency of the difference of total cost for these two design strategies.

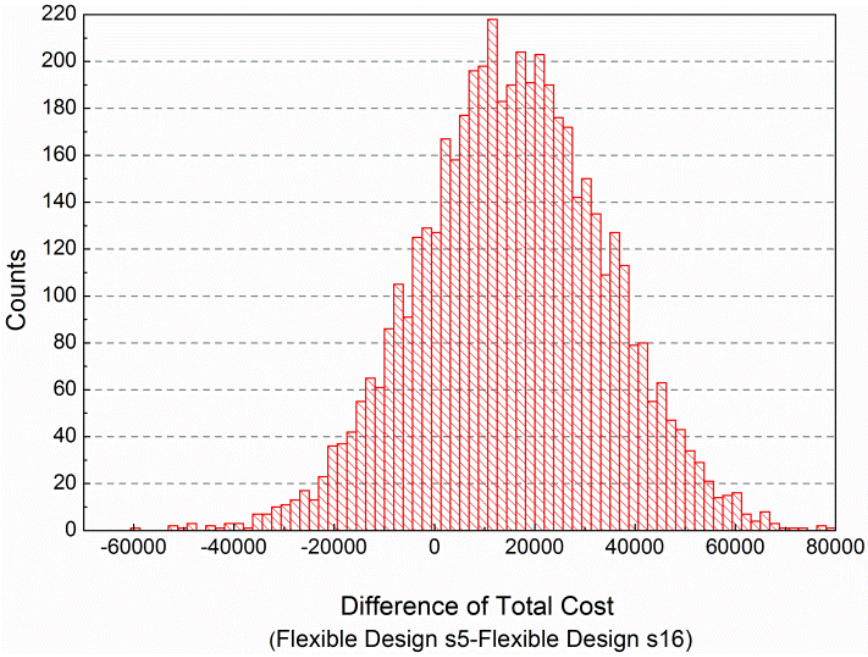


Fig 7.9 Frequency chart of NPV difference

To compare the risk susceptibility method and the sensitivity-based method, we further simulate the economic performance of flexible design in s_{12} which is selected by sensitivity-based method, as well as flexible design in s_5 which is recommended by risk susceptibility method, under scenario 1 with a high degree of uncertainty. Fig 7.10 shows a histogram of expected value of the total cost for these two strategies. The results demonstrate that the expected total cost of flexible design in s_5 is less than that of flexible design in s_{12} in the four scenarios. It proves that the risk susceptibility method is superior to sensitivity-based method, since the effect of change propagation for exercising flexibility is considered.

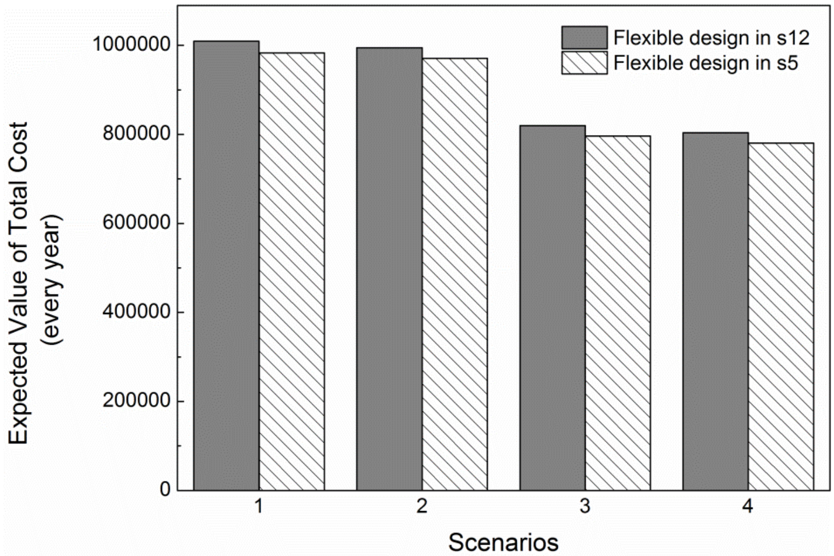


Fig 7.10 Expected value of total cost for flexible design in s_{12} and s_5

The results show that the system elements which are selected by the risk susceptibility method are worthy for flexibility. However, the accuracy of the results depends on the sample size. To illustrate the overall system performance and discuss the accuracy of the results, a further hypothesis testing is conducted. The null hypothesis H_0 is defined as the expected total cost of flexible design in s_{16} ($EC_{s_{16}}$) is larger than or equal to that of the fixed design (EC_{fix}), under scenario 3 with high degree of uncertainty, while the alternative hypothesis H_A is defined as $EC_{s_{16}} < EC_{fix}$. A standard one-tail z-test (two samples for mean) is conducted to compare the expected value of the two samples (5000 times simulation for each sample). The result of the z-test with 99% significance level yields z=-139.82 (p<0.01). This result is strongly suggestive that null hypothesis is rejected. In addition, A same z-test is conducted between the sample of flexible design in s_5 and the fixed design, under the same condition (i.e. scenario 3 with a high degree of uncertainty) and using the same number of simulation replication (i.e. 5000 times). The result of the z-test yields z=-86.48 (p<0.01). Therefore, the sample data provide sufficient evidence to conclude that the expected cost of flexible design in s_5 is less than that of the fixed design. The discussion here also shows that 5000 simulations for each sample are enough to guarantee the accuracy of the results.

7.5.2 Sensitivity Analysis

Based on the discussion above, we observe that the strategy of flexible design in s_{16} is an optimal design under different scenarios with high degree of uncertainty. The simulation results depend on some assumptions in the economic model. In practice, decision makers will likely change these assumptions and they may be interested in the effect of change. Here, we conduct a two-way sensitivity analysis of the parameters: cost of opting for design variable s_{16} and combined conditional probability for design variable s_{16}. The goal of this sensitivity analysis is to identify the threshold that triggers different design decisions between inflexible design strategy and strategy of flexible design in s_{16}, by modifying the parameters.

Fig 7.11 shows the results of the two-way sensitivity analysis in scenarios 1, 2, 3, and 4. In each scenario, diagonal hash areas represent the parameter combinations where the flexible design in s_{16} is favorable over the inflexible design. Blank areas represent the parameter combinations where inflexible design is better. Two important observations can be found in this sensitivity analysis. First, the flexible design outperforms the inflexible design when the parameter combinations are in the left-top corner. Second, the value of flexibility will be less than the cost of options, when the cost of option is more than 50% of the initial cost. Therefore, the inflexible design will be always selected under this situation, no matter what is the setting of combined conditional probability. The results of sensitivity analysis provide a guideline for decision makers to handle the problem of how much flexibility should be embedded in.

To see the sensitivity of the discount rate, additional simulations have been conducted for values ranging from r=6% to 20%. For each value of the discount rate, the expected total cost of flexible design in S_{16} under scenario 1 is derived, as shown in Table 7.10.

Table 7.10 Sensitivity analysis of discount rate for flexible design in s_{16}

Discount rate	6%	7%	8%	9%	10%	15%	20%
Expected Cost ($)	1,044,816	1,021,353	963,403	934,585	871,271	760,384	687,732

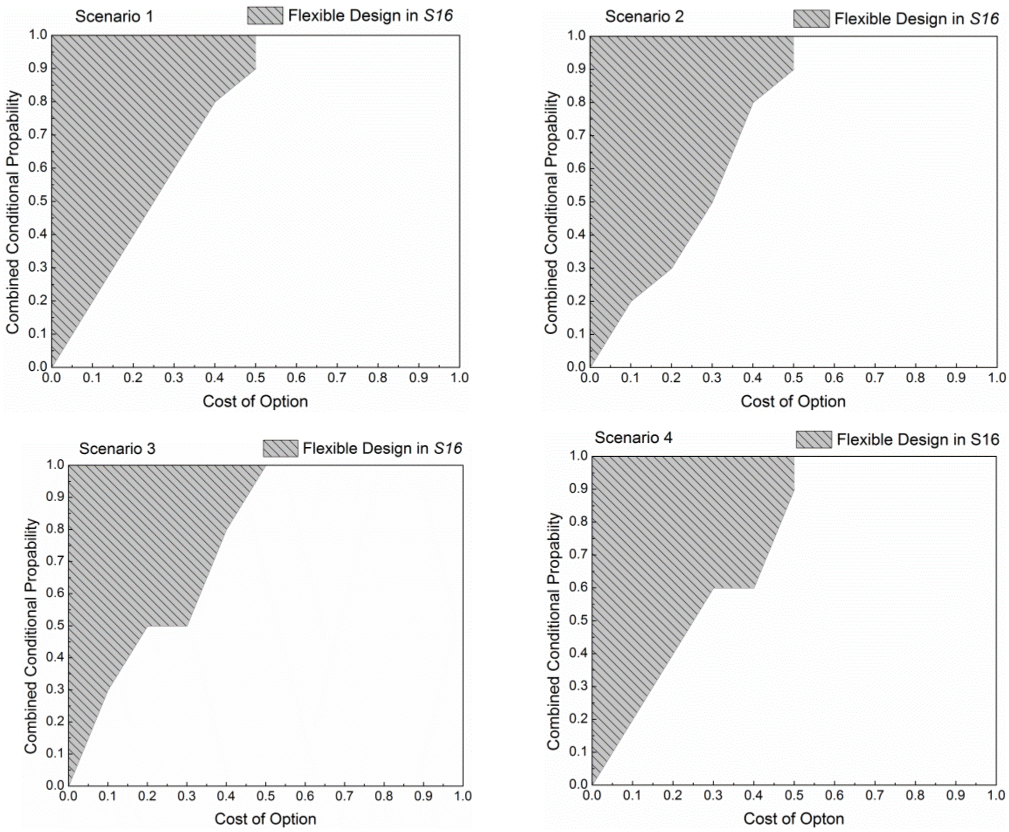


Fig 7.11 Two-way sensitivity analysis for flexible design in s_{16} under scenarios 1, 2, 3 and 4

Table 7.10 shows that the expected total cost decrease with the increase of a discount rate. This because that a flexible design could benefit from deferring the decision at a higher r. This could decrease capital and operating costs in present value terms. In addition, it also shows that the expected cost of flexible design in s_{16} is less than that of inflexible ($1,009,280) under scenario 1 when the discount rate is larger than 7%.

7.6 Summary

This chapter evaluates the risk susceptibility method through a case study on the railway signal system. The exogenous uncertainties, parameter-level design variables as well as complex influence relationships of the railway signal system are analyzed. According to risk susceptibility method, design variable of CTC (s_{16}) is the most suitable opportunity to embed a flexible option, followed by design variable of block length (s_5). In this case, four development strategies, namely inflexible design, flexible design in s_5, flexible design in s_{12}, flexible design in s_{16}, are modeled. The economic performances of these development strategies are simulated under four scenarios with different degrees of uncertainty. Results show that the value of flexibility would increase as uncertainty increases. This may provide guidelines for designers to respond to exogenous uncertainty. In addition, the flexible design opportunity which is selected by the risk susceptibility method is superior to others. This implies that embedding flexible options in this opportunity can significantly improve system performance under high uncertainty environment.

Chapter 8 Conclusion and Future Work

This thesis addresses the research opportunity of identifying flexible design opportunities for complex engineering system during the initial design phase. In this chapter, we will summarize the main results and contributions of this research and discuss the possible future extensions.

8.1 Conclusion

After a comprehensive discussion of existing work in system design theories and mythologies, three research opportunities are found: 1) How to model and select design concept of a complex engineering system in an intuitive way; 2) How to take into account multiple exogenous uncertainties and manage change propagation in the process of identifying flexible design opportunities; and 3) How to evaluate the proposed methodologies in a real engineering system.

The first research question is addressed in Chapter 3. A Pareto Set-based Concept framework has been proposed for system concept generation and selection. This PSBC framework maps multiple objectives of design concept into Utility-Cost space by using Multi-attribute Tradespace Exploration. A set of design alternatives in the Pareto frontier is selected to model the performance of the design concept. Compared to existing work in the multi-objective setting, the PSBC framework provides quantitative and qualitative understanding of the tradeoffs for a design concept. It helps designers to select competitive design concepts. To comprehensively illustrate the PSBC framework, a numerical example of airport transportation system design problem has been done. Three design concepts for the Chicago transportation system have been intuitively displayed in the Utility-Cost tradespace. The optimal design concept is selected and discussed for different criteria.

Chapter 4 and Chapter 5 focus on the research question of how to identify the elements in a complex engineering system that might most be worthy to be considered for flexibility. The sensitivity-based method which is proposed in Chapter 4 extends the existing works by considering multiple exogenous uncertainties in the flexible design concept generation process. Specifically, it is proposed for searching influence paths from exogenous uncertainties to system elements. The exogenous uncertainties which directly or indirectly trigger the changes of system elements are counted, in order to help designers determine valuable design opportunity. Although the sensitivity-based method improves existing methods by simultaneously simulating multiple exogenous uncertainties, it simplifies the operating environment by making some assumptions. For example, the degree of dependency between the system elements are the same, and the costs of switching the system elements from one state to another are the same. If these assumptions hold, the sensitivity-based method is a straightforward and effective method to generate flexible design concept. It serves as a preliminary work of the research question on identifying flexible design opportunities.

Departs from Chapter 4, the risk susceptibility method which is proposed in Chapter 5 is a more generic method. The goal of this research work is to extend sensitivity-based method by removing assumptions and provides a more realistic modeling. The risk susceptibility method also aims to identify quantitatively valuable opportunities to embed flexibility in complex engineering system design. This methodology integrates Bayesian network methodology into the engineering system design, and effectively models complex change propagation within multiple domains of an engineering system. It builds upon existing methodologies, which only consider direct neighboring relationships in the generation of flexible design concepts. The proposed methodology selects and ranks a set of system elements by predicting and analyzing the risk of change propagation. The ranking information of system elements can help to limit the number of flexible design concepts to consider and analyze at an early conceptual stage, in contrast to other concept generation methods available in the literature. Furthermore, the ranking information provides clear guidance to designers and decision-makers, especially when they have limited analytical resources available.

Research work in Chapter 6 and Chapter 7 focuses on the evaluation problem. In this thesis, High-Speed Rail (HSR) system is analyzed to further illustrate and validate the proposed methods. In Chapter 6, flexible design opportunity for HSR system is selected in subsystem-level by using the sensitivity-based method. Three design variables: “in-station facilities”, “signal system”, and “control system” are identified for embedding flexibility. Three development strategies for “in-station facilities” are generated and compared under travel demand uncertainty. The result shows that the flexible strategy has 13.6% improvement over the fixed strategy. This result proves that adding flexibility in engineering system by using sensitivity-based method can improve system performance, compared with inflexible design. In Chapter 7, we limit our resources to analyze a subsystem of HSR system—the railway signal system. It is analyzed in parameter-level by using the risk susceptibility method. Four development strategies are modeled under several scenarios with different degrees of uncertainties. The result is consistent with findings of earlier studies that the value of flexibility would increase as uncertainty increases. In addition, results also show that the flexible design opportunity which is selected by the risk susceptibility method is superior to the one which is recommended by sensitivity-based method. This implies that managing change propagation in the flexible engineering design can further improve system performance.

8.2 Future Work

This research has addressed some new challenges in flexible engineering system design. However, some limitations remain in the proposed methods and applications. Here, we raise the following research issues which we believe are interesting future works.

The first research issue relates to the risk susceptibility method. In the proposed method, the arcs in the Bayesian network with less information are removed when cyclic occurs. The aim is to eliminate possible cyclic dependency and make the representation of an engineering system suitable for the Bayesian network analysis. Since cyclic dependency is an essential feature of the engineering system, the elimination of feedback loops in the engineering system may slightly impact the solution. One of the potential ways to improve the proposed methodology is to model the complex dependencies using the dynamic Bayesian network. The dynamic Bayesian network adds the temporal dimension into the standard Bayesian network model. The change of the system can be modeled in a series of time slices and every time slice of a model corresponds to one particular state of a system. In general, the change propagation between the system elements may have a time delay. Therefore, it is reasonable for us to model the change impact of one system elements in a subsequent time slice. The advantage of using the dynamic Bayesian network is that the cyclic dependency can be analyzed in the modeling process and no loops may occur in one time slice. Even though determining and analyzing the time delay for the change propagation require deep domain knowledge and time consuming, it is valuable to conduct a deep discussion and model the complex relationships with the dynamic Bayesian network.

The second research issue relates to the application domain. In order to evaluate and illustrate the proposed method, a HSR system design problem has been investigated. Since the HSR system shares key characteristics with other complex engineering systems, it is claimed that HSR system can serve as a representative example to evaluate the proposed method. We also believe that the proposed method can be reproduced for different systems when clearly identify exogenous uncertainties and interdependencies. However, this aspect needs to be validated further.

The third research issue relates to the evaluation metrics and evaluation strategy. In this thesis, the anticipated performances of design strategies are the net present value of total costs and the expected value of total costs. As the economic metrics are very important for engineering system, a research on comprehensive economic metrics should be conducted in the future. This comprehensive economic metric may consider most of the important cost and benefit for stakeholders, such as jobs provide to the local economy. In terms of the evaluation strategy, the results of risk susceptibility method are just compared with that of sensitivity-based method and inflexible design strategy in this thesis. It should be valuable to compare the proposed method with other existing works, such as CPA by Suh et al., (2007), prompting and explicit training by Cardin et al., (2012), or the IRF by Mikaelian et al., (2011, 2012) to determine which ones are most effective, depending on context and resources.

The fourth research issue relates to the data collection in the case studies. The HSR system studied in this thesis is relatively simple with only a few coupled parameters. For example, only 3 exogenous uncertainties and 17 design parameters are analyzed and investigated in the second case study. However, the structure and interdependency of the real HSR system are more complex. It should be interesting to further evaluate and validate the proposed method trough a more complicated case. Furthermore, most of the data used in these two case studies are extracted from existing research papers; however, assumptions still exist. For example, the switching cost of each design variable is assumed as 20% of their capital cost in Chapter 7. The assumptions simplify the real situation, since a certain value of switching cost is set for each design variable. In fact, the switching cost of a design variable may be different based on different forms of flexibility. Therefore, it should be meaningful to replace the assumption with the real data in the future when this information can be obtained.

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