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A System-of-Systems Framework for Assessment of Resilience in Complex Construction Projects

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A SYSTEM-OF-SYSTEMS FRAMEWORK FOR ASSESSMENT OF RESILIENCE IN COMPLEX CONSTRUCTION PROJECTS

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We have read this dissertation and recommend that it be approved.

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ABSTRACT OF THE DISSERTATION

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Uncertainty is a major reason of low efficiency in construction projects. Traditional approaches in dealing with uncertainty in projects focus on risk identification, mitigation, and transfer. These risk-based approaches may protect projects from identified risks. However, they cannot ensure the success of projects in environments with deep uncertainty. Hence, there is a need for a paradigm shift from risk-based to resilience-based approaches. A resilience-based approach focuses on enhancing project resilience as a capability to cope with known and unknown uncertainty. The objective of this research is to fill the knowledge gap and create the theory of resilience in the context of complex construction project systems.

A simulation approach for theory development was adopted in this research. The simulation framework was developed based on theoretical elements from complex systems and network science. In the simulation framework, complex projects are conceptualized as meta-networks composed of four types of nodes: human agents, information, resources, and tasks. The impacts of uncertainty are translated into perturbations in nodes and links

in project meta-networks. Accordingly, project resilience is investigated based on two components: project vulnerability (i.e., the decrease in meta-network efficiency under uncertainty) and adaptive capacity (i.e., the speed and capability to recover from uncertainty). Simulation experiments were conducted using the proposed framework and data collected from three complex commercial construction project cases. Different scenarios related to uncertainty-induced perturbations and planning strategies in the cases were evaluated through the use of Monte Carlo simulation.

Three sets of theoretical constructs related to project resilience were identified from the simulation results: (1) Project vulnerability is positively correlated with exposure to uncertainty and project complexity; (2) Project resilience is positively correlated with adaptive capacity, and negatively correlated with vulnerability; (3) Different planning strategies affect project resilience either by changing the level of vulnerability or adaptive capacity. The effectiveness of a planning strategy is different in different projects. Also, there is a diminishing effect in effectiveness when adopting multiple planning strategies. The results highlighted the significance of the proposed framework in providing a better understanding of project resilience and facilitating predictive assessment and proactive management of project performance under uncertainty.

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1. INTRODUCTION

1.1 Background

Low efficiency in projects performance is a major challenge in the construction industry. A large number of construction projects are shown to be unable to meet their performance objectives in terms of time and cost. Based on a study of 258 transportation infrastructure projects across 20 nations, 9 out of 10 transportation projects fall victim to cost escalation (Flyvbjerg, Skamris holm, & Buhl, 2003). According to another recent study conducted by the Construction Industry Institute (CII), only 5.4% of the 975 construction projects reviewed met their performance predictions in terms of cost and schedule within an acceptable margin, while nearly 70% of these projects had actual costs or schedule exceeding +/- 10% deviation from their authorized values (Figure 1-1) (CII, 2012). Performance failures such as cost overruns and time delays continue to be the major concern of researches and practitioners in the construction industry because of their deleterious effects on the efficiency of investments and sustainable development. Examples of failed, large complex projects include the Channel Tunnel connecting Great Britain and France that was one year behind schedule and $6 billion over budget when completed, and the Boston Central Artery project that was completed nearly 10 years late at a cost overrun of more than $10 billion (Cisse, Menon, Segger, & Nmehielle, 2013).

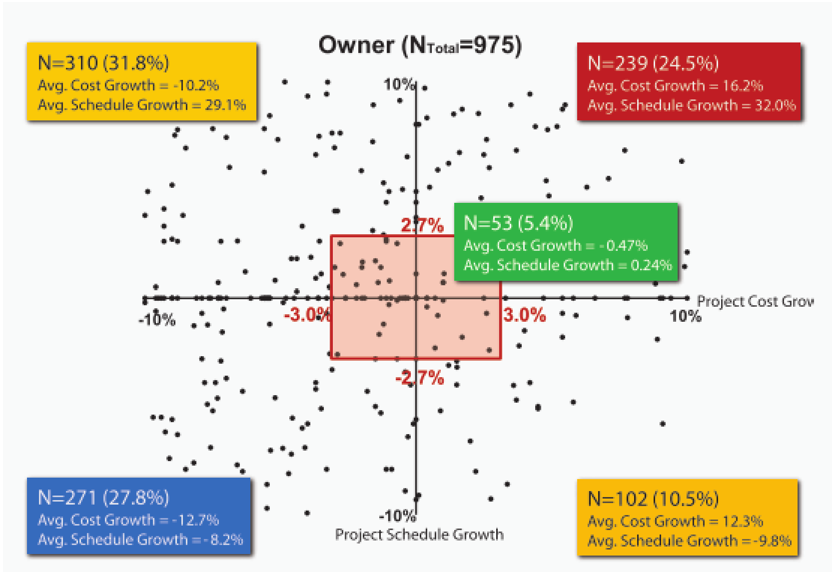


Figure 1-1 Performance Assessment of 975 Owner-submitted Construction Projects (Construction Industry Institute, 2012)

A dollar saved as a result of enhanced project performance could be spent to build more projects to better satisfy people's needs. For example, a dollar spent on additional infrastructure construction produces roughly double initial spending in ultimate economic output in the short term and, over a 20-year period, produces an aggregated $3.20 of economic activity (Cohen, Freiling, & Robinson, 2012). Considering the $1.73 trillion size of the construction industry (United States Census Bureau, 2007), the cost savings resulting from enhanced performance will lead to significant economic outcomes both in the short and long terms.

1.2 Problem Statement

Over the past few decades, project management tools and technologies have been created to improve the performance of construction projects. Despite the efforts made to enhance their performance, construction projects still suffer from low efficiency. One of the important obstacles in improving the efficiency of construction projects is the disparity between the existing theories in performance assessment and the complex and uncertain nature of modern construction projects. This knowledge gap creates the need for a paradigm shift in performance assessment approaches. In particular, better understanding and improving the ability of project systems to cope with uncertainty is an important element in enhancing performance in complex projects. To address the limitations in the existing literature and facilitate the paradigm shift, this study investigates resilience in project systems as the ability of project systems to cope with uncertainty.

In this study, complex construction projects are conceptualized as complex systems. Accordingly, theoretical underpinnings from complex system science are adopted in order to propose an integrated framework for performance assessment in construction project systems. Resilience is an emergent property in a complex system which is related to a system's capability in coping with uncertainty. Resilience arises from dynamic behaviors and interdependencies in complex systems. Understanding of the determinants of resilience in project systems is essential in improving project performance under uncertainty. However, the current literature in project management and construction has an important gap related to characterizing and examining resilience in construction project systems. Figure 1-2 shows how the knowledge gap is identified and leads to this research at the interface of construction project management theories and complex system theories. These knowledge gap areas will be discussed in detail in the following section.

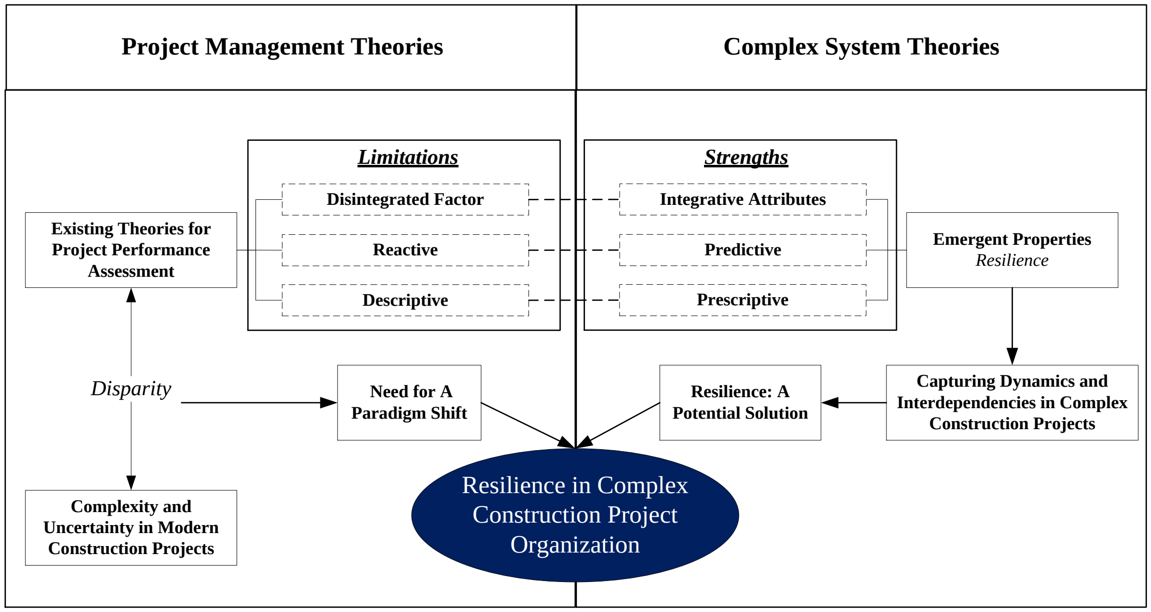


Figure 1-2 Knowledge Gap

1.2.1 Knowledge gaps

Traditional performance assessment and project management approaches (so called "PM 1.0") in construction projects are rooted in a reductionism perspective toward projects (He, Jiang, Li, & Le, 2009). This reductionism perspective considers construction projects as monolithic systems, which are "a set of different elements connected or related so as to perform a unique function" (Rechtin, 1991). Considering construction projects as monolithic systems, the majority of the studies related to performance assessment regard a construction project as an assemblage of processes and activities and view a project statically (Lyneis, Cooper, & Els, 2001). In one stream of research, the success or failure of construction projects are investigated based on the attributes of individual process and/or constituent in projects (e.g., D. W. M. Chan & Kumaraswamy, 1996; A. P. C. Chan, Ho, & Tam, 2001; Iyer & Jha, 2005). Examples of these attributes include *quality of site management and supervision, experience of contractors, skills of labors, availability of* *materials and equipment*, *subcontractors' work*, *financial conditions of owners*, and the *competence of project managers*. In this stream of research, the relationships between individual attributes and project performance outcomes are studied. The main limitations of studies in this stream of research are their *deterministic* and *descriptive* traits. In existing studies of this stream, the difference related to the level of complexity and uncertainty in projects has not been fully considered. From the perspective of this stream of research, the attributes leading to success of a project are deterministic regardless of the level of complexity and uncertainty. These attributes of projects identified based on the one-size-fits-all approach can explain why a project succeeded. However, they cannot be used for organizing projects to ensure successful outcomes under different levels of complexity and uncertainty. Thus, the results of studies in this stream are mainly descriptive rather than prescriptive.

In another stream of research, studies have been conducted to investigate the impacts of risks and uncertainties on the ultimate performance outcomes of projects (e.g., Baloi & Price, 2003; Zou, Zhang, & Wang, 2007; Zayed, Amer, & Pan, 2008). Different sources of risk and uncertainty (e.g., *variations from the clients*, *unexpected site conditions*, *weather conditions*, *price fluctuations of construction materials*, *staff turnover*) and their impacts on project performance outcomes are assessed in this stream of research. Although this stream of research has emphasized the significance of risks and uncertainties on project performance outcomes, the interactions between projects and the uncertain environments are not considered. The complexities of projects as well as their individual and integrative attributes affect their abilities to cope with uncertainty. Different projects exhibit different behaviors in the face of uncertainty. Existing literature related to this stream does not provide any insight on how to proactively design projects across different levels of complexity which are capable of successfully operating in uncertain environments.

The literature on contingency theory, as another stream of research, provides a new perspective on understanding and assessing the performance of projects. Contingency theory is based on the principle that all possible ways of organizing are not equally effective. The contingency theory contains a basic assumption that a fit of the organization characteristics to contingencies that reflects the situation of the organization directly affects the performance outcomes (Donaldson, 2001). Researchers have been able to use the contingence theory to better understand project performance and design projects (Levitt et al., 1999; Shenhar, 2001). The contingency view of projects includes both the macro and micro dimensions (Mealiea & Lee, 1979). At the macro level, congruence should be achieved at the interface of the environmental requirements and the organizational structure of a project. At the micro level, the impact of the congruence between the project organizational structure and the individual micro behaviors on the project performance is considered. While contingency theory has addressed some of the limitations of the other streams of research pertaining to performance assessment in projects, it provides two disintegrated sets of theories for assessment of project performance. This limitation is in part due to the lack of consideration of the integrative attributes that arise as a result of the interactions between different processes and factors in the existing theories of project performance assessment.

In summary, the existing studies related to project performance assessment are *disintegrated*, *reactive* and *descriptive*. Integrated theories for predictive assessment and proactive management of projects with high level of complexity and uncertainty are still missing. One of the reasons is that the PM 1.0 style of performance assessment fails to abstract construction projects at an appropriate level, in which the complex and dynamic behaviors can be captured. The PM 1.0 style has proved to be efficient only in analyzing projects in the relatively stable political, economic and technological context of the post-World War II period (Levitt, 2011). Modern construction projects are large, complex projects operating in dynamic environments. These complex construction projects are composed of different interrelated processes, activities, players, resources, and information. Changes in one or several constituents of a project can cause unforeseen changes in other constituents of the project, and the causal feedback between different constituents cause the project to evolve over time (Taylor & Ford, 2008). The traditional tools and methods for performance assessment have been proven to be incapable of capturing these dynamics and interdependencies in modern construction projects (Levitt, 2011; Love, Holt, Shen, Li, & Irani, 2002). Hence, there is a need for a paradigm shift and new theories in performance assessment based on a better understanding of the underlying dynamics and interactions in construction projects affecting their resilience to uncertainty.

1.2.2 Complex system theory and system resilience

Over the last decade, a new paradigm in the project management field (so called "PM 2.0") has emerged toward agile project management for modern, dynamic and complex projects in the twenty-first century (Levitt, 2011). The PM 2.0 paradigm aims at providing new tools and techniques for effective management of complex projects. Toward PM 2.0 paradigm, Zhu & Mostafavi (2014c) have suggested that complex projects demonstrate the distinguishing traits of complex systems, more specifically, system-of-systems, and hence, should be conceptualized and analyzed as complex systems. Different from monolithic systems, the behaviors of complex systems are greatly affected by the dynamics and interdependencies of the systems. One of the distinguishing traits of complex systems is the existence of emergent properties. Emergent properties stem from interactions between the components of complex systems and the environment (Johnson, 2006). According to Sage & Cuppan (2001), emergent properties function and carry out purposes that are not possible by any of the components of the complex systems. Hence, emergent properties have a significant impact on the performance of complex systems. The understanding of complex construction projects as complex systems and recognizing the significance of emergent properties provide an innovative theoretical lens and methodological structure toward the creation of tools and techniques for integrated performance assessment in construction projects. It is a critical step and has great potential for creating integrated theories for performance assessment and making a paradigm shift toward PM 2.0 in the practice of construction management.

One of the key emergent properties recognized in project systems as well as other complex systems is resilience. As other emergent properties, resilience is an integrative property of complex systems which is aggregated from dynamic behaviors and interdependencies between constituents in systems, but cannot be attributed to any single constituents. The concept of resilience has its roots in ecology through studies of interacting populations like predators and prey and their functional responses in relations to ecological stability theory in the 1960-1970s, and then it has been widely examined in the context of socio-ecological systems (Folke, 2006). Recently, more studies related to resilience have been conducted in the context of different types of complex systems (e.g., critical infrastructure systems, organizational systems, and economic systems) (Francis & Bekera, 2014; Lengnick-Hall, Beck, & Lengnick-Hall, 2011; Perrings, 2006). Table 1-1 summarizes the definitions of resilience from different disciplinary perspectives. Although a universal understanding of resilience is still missing in different streams of studies, some key characteristics related to resilience could be observed from those definitions. First, resilience is closely related with uncertainty. In definitions of resilience from different disciplines, key words such as changes, surprises, shocks and disruptive events can be found. Resilience is not a system property which exhibits in the business-as-usual conditions; instead, it is a measure of a system's capability to cope with uncertainty. Second, the level of resilience of a complex system greatly affects the efficiency or functionality of the system. As explained in some of the definitions, a high level of resilience is expected to reduce the magnitude and/or duration of disruptive events which potentially threaten survival of the systems.

Table 1-1 Definitions of Resilience from Different Disciplinary Perspectives

Context	Definition of resilience
Ecosystem	Resilience determines the persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters. (Holling, 1973)
Social system	The ability of groups or communities to cope with external stresses and disturbances as a result of social, political and environmental change. (Adger, 2000)
Social-ecological system	Resilience is the capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedback. (Walker, Holling, Carpenter, & Kinzig, 2004)
Economic system	The ability of the system to withstand either market or environmental shocks without losing the capacity to allocate resource efficiently (the functionality of the market and supporting institutions), or to deliver essential services (the functionality of the production system). (Perrings, 2006)
Infrastructure system	Infrastructure resilience is the ability to reduce the magnitude and/or duration of disruptive events. The effectiveness of a resilient infrastructure or enterprise depends upon its ability to anticipate, absorb, adapt to, and/or rapid recover from a potentially disruptive event. (National Infrastructure Advisory council (NIAC), 2009)
Organizational system	Organizational resilience is defined as a firm's ability to effectively absorb, develop situation-specific responses to, and ultimately engage in transformative activities to capitalize on disruptive surprises that potentially threaten organization survival. (Lengnick-Hall et al., 2011)

A project is a temporary organizational system (Turner & Müller, 2003). Various studies (e.g., Weick & Sutcliffe, 2007; Sutcliffe & Vogus, 2003; Robert et al., 2010) have emphasized the significance of resilience in enhancing the performance of organizations and stressed the urgent need for theory development in this area. The concept of resilience, which is originated in complex system theories, has the potential to address the gaps in the body of knowledge of the construction project management field. First, resilience is an integrative attribute which arises from the micro behaviors and interactions in projects. It captures the dynamics and interdependencies in projects and reflects them on the macro-level project performance. Second, resilience can be used as a leading indicator to provide predictive assessment and guide design of projects toward better performance outcomes. Unlike traditional approaches that attempt to anticipate unexpected events and mitigate performance risks, resilience recognizes the inherent fallibility of project systems and attempts to understand how projects maintain and recover their performance in the face of uncertainty (Vogus & Sutcliffe, 2007). Hence, a project may have a better chance of success if a resilience-based approach is adopted, in which the project's level of resilience is proactively monitored and is in congruence with its level of complexity and uncertainty. Thus, the theory of resilience could make a paradigm shift from the conventional approaches in dealing with complexity and uncertainty in construction projects. Despite the potential significance of resilience on project systems' performance outcomes, existing understanding on resilience of project systems remains limited.

1.2.3 From risk-based to resilience-based approaches

A review of the existing literature highlights the limitations of the conventional project management theories in providing ways to minimize the impacts of uncertainty on the performance of construction projects. The traditional approaches in dealing with uncertainties in project management start with risk identification (so called "risk-based" approach). The risk-based approaches focus on minimizing the risks of failures by investing in mitigation and transfer mechanism to enable "fail-safe" projects. "Fail-safe" projects are designed for protecting projects from identified risks. Different risk assessment and management (RAM) procedures and models have been developed in the construction industry following the traditional risk-based approaches (Akintoye & MacLeod, 1997; Mulholland & Christian, 1999; Fung, Tam, Lo, & Lu, 2010). However, some of the uncertain risks emerge from interactions and independencies between different constituents in projects during construction, which are hard to be identified and estimated beforehand. The evidence from a large number of construction projects informs us about the inherent fallibility of construction projects and inability of the conventional risk-based approaches to enable successful projects. In contrast to the conventional risk-based approaches, resilience-based approaches admit the inherent fallibility of project systems and focus on enhancing the capabilities of projects to cope with uncertainty (Jeryang Park, Seager, & Rao, 2011). The resilience-based approaches enable "safe-to-fail" projects, which adopt design and management strategies for projects to respond to unknown and unexpected risks. Hence, it is argued that resilience-based approaches are urgently needed to enable a paradigm shift in the existing project management and performance assessment theories to avoid, or minimize, the debilitating impacts of uncertainty on project performance. Unfortunately, there is an important gap in knowledge pertaining to an integrative theory of project resilience and the ways to reduce the impacts of uncertainty on construction projects.

1.3 Research Objectives

The overarching objective of this research is to gain a better understanding of the principle phenomena affecting resilience (i.e., projects' ability to cope with uncertainty) of project systems. To achieve the overarching objective, this research aims to accomplish three specific objectives:

Objective #1: *Understand and quantify project vulnerability (i.e., projects' susceptibility to uncertainty) and its correlation with project exposure to uncertainty and project complexity.*

Project vulnerability is one important component of resilience. The first objective of this research is to investigate the level of vulnerability of project systems to various sources of uncertainty based on the exposure to uncertainty as well as project complexity. The relationships between project exposure to uncertainty and vulnerability, and project complexity and vulnerability are studied. Possible approaches to mitigate project vulnerability are evaluated.

Objective #2*: Understand and quantify the impacts of project vulnerability and adaptive capacity on project schedule performance and resilience under uncertainty.*

A project system's overall capability in coping with uncertainty is not only affected by its level of vulnerability, but also its capacity to quickly adapt to changes and recover from the negative impacts of uncertainty. The second objective of this research is to investigate project's overall capability in coping with uncertainty based on both vulnerability and adaptive capacity of a project system. In this study, project schedule performance is selected as a key performance indicator (KPI) for measuring resilience. Thus, the relationships between project vulnerability, adaptive capacity, and schedule deviation under uncertainty are studied.

Objective #3*: Evaluate the effectiveness of planning strategies in enhancing project resilience.*

The third objective of this study is to evaluate the effectiveness of a list of planning strategies that can potentially enhance project resilience in the face of uncertainty. Those planning strategies can either reduce project vulnerability, or increase project adaptive capacity. In this study, the effectiveness of single planning strategies and their joint effects are quantified and evaluated.

Achieving these research objectives would improve our understanding of the links between *planning strategy*, *complexity*, *vulnerability*, *adaptive capacity*, *resilience*, and *performance outcomes* in construction projects under uncertain environments. Understanding these links also enables creation of integrated theories and predictive management tools to proactively improve resilience in complex construction projects. Hence, this research addresses a critical step toward improving project performance in uncertain environments. By achieving the research objectives, new knowledge in the field of construction project performance assessment and management could be developed. Decision-makers in construction projects could use the knowledge to design more resilient projects to enhance the performance measures under dynamic, complex, and uncertain conditions.

1.4 Research Framework and Roadmap

To achieve the research objectives, a simulation approach for theory development is adopted. According to Davis, Eusebgardt, & Binghaman (2007), a simulation approach is an effective method for theory development when: (i) a theoretical field is new, (ii) the use of empirical data is limited, and (iii) other research methods fail to generate new theories in the field. These traits are consistent with this specific study. First, the theoretical field related to resilience in project systems is a new field and is still developing. In particular, there are very limited theoretical constructs related to resilience in the context of construction projects. Second, investigation of construction project resilience based on empirical data is very difficult. In order to successfully investigate resilience using empirical data, a researcher should be able to expose projects to different perturbation scenarios, change the influencing variables, and measure the impacts on resilience and project performance. Conducting and replicating such empirical experiments would be nearly impossible in construction projects. Theory development using a simulation approach addresses these limitations, and thus is an ideal method for attaining the research objectives. A simulation approach enables building the computational representations of projects and conducting experiments based on different scenarios related to uncertainty-induced perturbations, planning strategies, and node entity attributes to test different hypotheses and build constructs that quantitatively link various theoretical elements. Figure 1-3 gives an overview of the research framework and roadmap following the steps in simulation research approach proposed by Davis et al. (2007).

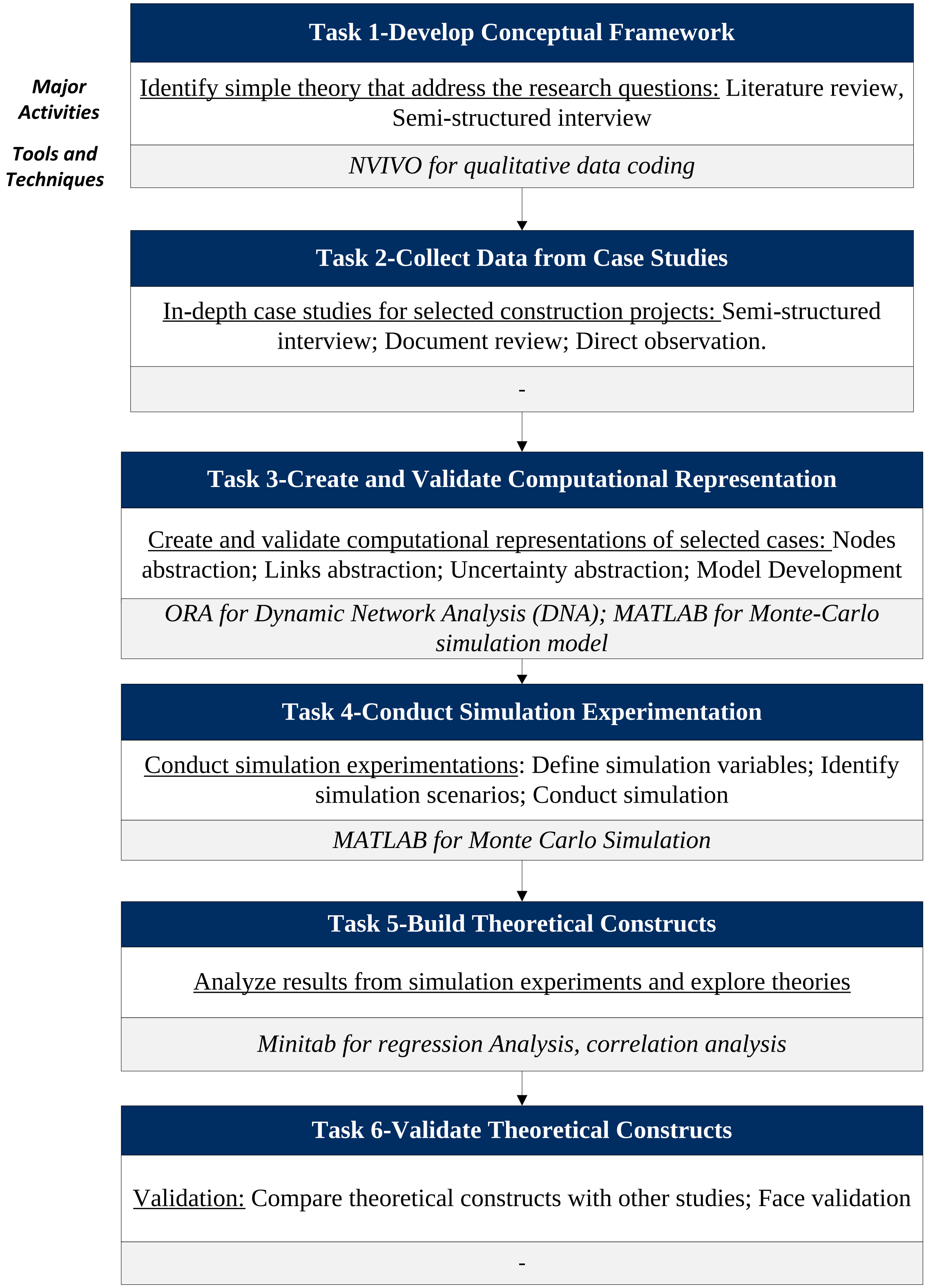


Figure 1-3 Research Roadmap

1.5 Organization of Dissertation

This dissertation follows the "multiple publication" format. Chapter 2, 3, 4 and 5 are published, submitted, or planned to be submitted for publication in peer-reviewed journals. Each of these chapters has its own introduction, methodology, case study, analysis and conclusions sections. Chapter 6 summarizes the findings, contributions, limitations and future work directions of this research. References of each chapter are listed as a whole at the end of this dissertation. Table 1-2 provides an overview of the purposes and major contents of each chapter.

Table 1-2 Purposes and Contents of Each Chapter

Chapter	Purposes	Major Contents
1	Introduction	Introduction of research background, questions, objectives, and approaches
2	Conceptualization	Development of a SoS conceptual framework for complex construction projects and an illustrative case study for framework implementation
3	Conceptualization	Identification of emergent properties in complex construction projects through interviews with senior project managers
4	Development of meta-network computational models	Development of a meta-network simulation framework to quantify project vulnerability and an illustrative case study for framework implementation
5	Case studies and theoretical constructs	Development of a comprehensive framework for investigation of project vulnerability, adaptive capacity, and schedule deviation under uncertainty; three case studies from real-world projects; and theoretical constructs developed from conducting simulation experiments and result analysis
6	Conclusion	Summary of this research, contributions, limitations and future work

2. INTEGRATED PERFORMANCE ASSESSMENT IN COMPLEX ENGINEERING PROJECTS THROUGH USE OF A SYSTEMS-OF-SYSTEMS FRAMEWORK

The objective of Chapter 2 is to propose a systems-of-systems (SoS) framework as an integrated methodological approach for bottom-up assessment in complex engineering projects. Two principles of systems-of-systems analysis (i.e., base-level abstraction and multi-level aggregation) are used to develop the proposed framework. At the base level, complex engineering projects are abstracted as various entities (i.e., human agents, resources, and information) whose attributes and interactions influence the dynamic behaviors of project systems. The performance of project systems at higher levels (i.e., activity level, process level, and project level) are then determined by aggregating entities at the levels below. Through the use of the proposed SoS framework, new dimensions of analysis for better understanding of the performance of engineering projects were explored. One application example of the proposed framework was demonstrated in a case study of a complex construction project. The findings highlight the capability of the proposed framework in providing an integrated approach for bottom-up assessment of performance in engineering projects.

2.1 Introduction

As temporary endeavors undertaken to create unique products, services, or results (Project Management Institute, 2013), engineering projects are ubiquitous across different industries, such as aerospace, marine, and construction. Over the last five decades, project management tools and techniques have been created to facilitate successful delivery of engineering projects. Despite the efforts made to enhance their performance, engineering projects are suffering from low efficiencies and a large portion of engineering projects are unable to achieve their initial goals. For example, in the construction industry a study conducted by the Construction Industry Institute (CII) revealed that out of 975 construction projects studied, only 5.4% of them met both performance goals in terms of cost and schedule within an acceptable margin, while nearly 70% of the projects had actual costs or schedules exceeding 10% deviation from their authorized values (Construction Industry Institute, 2012).

One important reason that hinders the traditional tools and techniques from better assessment and management of project performance is the conceptualization of engineering projects as monolithic systems. A monolithic system is a system composed of different elements for a single objective. Traits of monolithic systems include operational dependencies between elements, hierarchical structures, centralization, and static boundaries (Mostafavi, Member, Abraham, Delaurentis, & Sin, 2011; Mostafavi, Abraham, & Lee, 2012). Based on the conceptualization of engineering projects as monolithic systems, the majority of the existing tools and techniques in the project performance assessment and management field adopt a top-down approach towards assessment of monolithic systems. Tools and techniques based on the top-down approach focus on detailed, centralized planning, decentralized execution, and centralized control in management of engineering projects. This top-down approach has led to limitations in performance assessment and management of complex engineering projects (Levitt, 2011):

1. Lack of consideration of the autonomy of constituents in project systems (e.g., the ability of project sub-systems to make independent decisions or allow creativity and input from first-line personnel);
2. Lack of consideration of the micro-behaviors at the base-level of project systems (e.g., resource utilization, information processing, and decision making);
3. Lack of consideration of the interdependencies between different constituents (e.g., information exchange between different sub-systems);
4. Lack of consideration of emergent properties in project systems (e.g., project vulnerability, adaptive capacity, and resilience as integrative attributes arising from interdependencies and interactions in project systems); and
5. Lack of consideration of the evolving nature of project systems (e.g., the dynamic changes and evolvement of project systems over time).

Due to these theoretical and methodological limitations, the traditional paradigm in performance assessment and management has proven to be inefficient in managing modern engineering projects having high levels of complexity and uncertainty (Williams, 1999). Researchers have explored and implemented different methods, especially modeling techniques, to better understand and investigate complex projects in order to address the limitations in the traditional "top-down" approach. For example, agent-based modeling (ABM) has been used to capture the micro-behaviors and micro-interactives between human agents in a project (Levitt, 2012; Watkins, Mukherjee, Onder, & Mattila, 2009; Mostafavi et al., 2015). System dynamics (SD) has been used to explore the interdependencies and causal feedbacks between different constituents in a project (Taylor & Ford, 2008; Lyneis & Ford, 2007). Despite the efforts, a formalized framework that could guide the abstraction and implementation of a bottom-up approach for integrated performance assessment and management in complex projects is still missing (Alvanchi, Lee, & AbouRizk, 2011). Without a formalized framework for abstraction of project systems, models and methods used for assessment of project systems may not be comparable and thus not lead to creation of an integrated theory of performance assessment in projects. Thus, the objective of this paper is to propose a formalized framework as a new lens and methodological structure that leads to the creation and implementation of tools and techniques for integrated performance assessment and management in complex engineering projects.

To this end, a close examination of complex engineering projects is conducted in Section 2.2. The examination reveals that complex engineering projects are systems-of-systems (SoS) rather than monolithic systems. A SoS is “an assemblage of components which individually may be regarded as systems” (Maier, 1998). A SoS has different traits compared to a monolithic system and needs to be investigated based on those significant characteristics. Based on the identification of complex engineering projects as SoS, a formalized SoS framework for bottom-up assessment of project performance in engineering projects is proposed in Section 2.3. An example of application of the proposed framework is demonstrated in a complex tunneling construction project in Section 2.4. The results of the application example show the capabilities of the proposed framework in capturing the impacts of different base-level entities’ attributes on project performance through use of a bottom-up simulation approach. Finally, the conclusions and contributions of this study are discussed in Section 2.5.

2.2 Engineering Projects as Systems-of-Systems

Systems thinking is an effective way in the assessment and management of projects (Mostafavi et al. 2014; Sheffield, Sankaran, & Haslett, 2012; Locatelli, Mancini, & Romano, 2014; Ackoff, 1971). Based on system thinking, Model-Based System Engineering (MBSE) methodologies (e.g., IBM Harmony-SE, INCOSE Object-Oriented Systems Engineering Method) have been developed to better assess projects (Estefan, 2008). Different types of systems (e.g., monolithic system or system-of-systems) have different traits and need to be investigated using appropriate frameworks (Mostafavi et al., 2011). A successful analysis of projects using systems thinking is contingent on proper identification of the system type. Modern engineering projects are large, complex projects operating in dynamic environments. These complex engineering projects are composed of multiple interrelated systems, including different processes, activities, players, resources, and information. Changes in one system can also cause unforeseen changes in connected systems, and as a result the causal feedback between these systems causes projects to evolve over time. To better assess complex engineering project systems, an important step is to examine the traits of engineering projects to test whether engineering projects possess the attributes of SoS and thus should be investigated as such. Maier (Maier, 1998) proposed five distinguishing traits of SoS, including operational independence of individual systems, managerial independence of individual systems, emergent properties, evolutionary development and geographic distribution. Based on Maier's work, different existing studies have further discussed the significant traits of SoS (Sage & Cuppan, 2001; Lewis et al., 2008; A. Gorod, Sauser, & Boardman, 2008; Mostafavi and Abraham 2010). For example, Lewis et al. (Lewis et al., 2008) summarized the characteristics of SoS from different aspects, such as the degree of centralization, stakeholder diversity, operational independence, diversity of constituent systems, and control of evolution. In this study, the five distinguishing traits of SoS identified by Maier (Maier, 1998) were used to evaluate engineering project systems.

Operational Independence of Individual Systems: Operational independence means that the individual systems (i.e., sub-systems) of the SoS are capable of fulfilling their own functions and purposes independently (Sage & Cuppan, 2001). An engineering project usually includes different components such as finance, procurement, design, construction/production, risk management, safety management, and operation. Each of these components can be identified as a sub-system possessing its own purposes and functions and is capable of performing useful operations independently of each other. For example, in an aerospace project, different sub-systems exist for marketing, design, manufacture, and service (O'Sullivan, 2003). Each of these sub-systems consists of various entities (e.g., human agents, resources, information) conducting different activities in order to fulfill their independent functions. Different sub-systems are fully integrated in assemblage and product testing for the overall project success (O'Sullivan, 2003).

Managerial Independence of Individual Systems: Managerial independence implies that different project sub-systems are managed separately (Sage & Cuppan, 2001). In modern engineering projects, different sub-systems are separately developed and managed independently. In fact, because of the large scale and high complexity of modern engineering projects, it is nearly impossible for a single acquisition or command authority to conduct all the work or implement centralized control over the whole project. Each sub-system in an engineering project needs to be operated and managed independently by human agents with specific expertise and particular resources. For example, in a construction project, different subsystems (e.g., design, construction, contract administration, risk management) are independent operational units led by different stakeholders, such as the designer, contractor, and consultant. The successful operation of each sub-system needs support and cooperation from other sub-systems. However, each sub-system is managed and operated independently.

Emergent Properties: Emergent properties have been defined by Johnson (2006) as "behaviors that stem from interactions between the components of complex systems and the environment." Emergent properties are important traits of SoS. A SoS is more than the sum of its constituents as it possesses emergent properties that do not reside in any sub-systems (Sage & Cuppan, 2001). In complex engineering projects, different emergent properties (e.g., resilience, vulnerability, agility, and adaptive capacity) have been investigated (Augustine, Payne, Sencindiver, & Woodcock, 2005; Dalziell & McManus, 2004). These properties arise from dynamic behaviors and interdependencies of constituents, and cannot be attributed to any single constituent in project systems. For example, project adaptive capacity refers to a project's ability to adjust itself in terms of organizational structure or execution processes in response to undesirable disruption in order to maintain or enhance its performance outcomes (Dalziell & McManus, 2004). The level of adaptive capacity of a project is significantly affected by the interdependencies between different sub-systems. For instance, bureaucracy, which hinders the flow of information between different sub-systems in an engineering project, decreases a system's adaptive capacity by delaying the process of making adaptive changes in the project, thus leading to project performance deficiencies (Uhl-Bien, Marion, & McKelvey, 2007).

Evolutionary Development: A SoS has a dynamic and evolutionary nature. Development of SoS is evolutionary with structures, functions, and purposes added, removed, and modified over time (Sage & Cuppan, 2001). Complex engineering projects also experience evolutionary development during their lifecycles. Various factors from both internal and external environments cause changes in complex engineering projects. The common factors causing changes in projects include: project scope change due to client/user's requirements; change in economic, legal or social conditions; introduction of new technology; and force majeure (Construction Industry Institute, 2013; Keil, Cule, Lyytinen, & Schmidt, 1998). Due to these dynamic changes, new functions and project components may be added, while some of the original functions and components are removed. Using aerospace projects as an example, changes in project design and structure could be made if new technologies are developed. In complex engineering projects, changes in one sub-system cause changes in other interrelated sub-systems. For example, if a change is made in project engineering design, the procurement sub-system needs to make corresponding changes since different materials and equipment may be needed, thus requiring the production/construction sub-system to make corresponding changes because different methods may be used in production/construction. As a result, the final configuration and outcomes of an engineering project are usually totally different from its original plan due to the evolutionary development.

Geographic Distribution: Geographic distribution is another significant trait of SoS. The sub-systems in SoS are often geographically dispersed. The same phenomenon exists in modern engineering projects. In engineering projects, although the final products could be assembled in one location, different sub-systems (e.g., design, procurement, construction/production, research and development, and risk management) can operate at different geographic locations, sometimes in different cities or countries. Nowadays, under the trend of globalization of economies, geographic distribution can be seen more and more in engineering projects. With the help of advanced information and communication technology (ICT), different sub-systems in an engineering project can work together without the constraints of locations (Ahuja, Yang, & Shankar, 2009). For example, when the design sub-system and construction sub-system of a construction project are located in two different geographic locations, ICT tools such as building information modeling (BIM) facilitates coordination and collaboration between the two sub-systems in order to eliminate possible constructability problems.

The examination of these significant traits of SoS in the context of complex engineering projects shows that engineering projects are SoS and should be investigated as engineering project systems-of-systems (EPSoS). The traits of SoS bring various requirements for studying and managing EPSoS. For example, Gorod et al. (Alex Gorod, Gove, Sauser, & Boardman, 2007) proposed a SoS Operational Management Matrix, in which the requirements of SoS management were defined based on different traits of SoS. Some of the requirements include considering autonomous behaviors, observing information from sub-systems in SoS, and allowing for optimum path of emergence (Alex Gorod et al., 2007). Accordingly, there are specific requirements that need to be considered in the analysis framework for EPSoS. First, a proper level of abstraction is required for analysis of EPSoS due to the operational and managerial independence of individual sub-systems in EPSoS. Traditionally, the level of abstraction in analysis of engineering projects is at the process or activity level (Williams, 1999). Hence, the impacts of the dynamic behaviors, uncertainty and interdependencies of entities below the process or activity level cannot be captured. However, each of the sub-systems in EPSoS includes various entities (e.g. human agents, resources, and information) and their dynamic behaviors and interactions directly affect project performance (Sheffield et al., 2012). Therefore, a proper level of abstraction which facilitates investigating the attributes of entities, their dynamic behaviors and interdependencies is needed for a better understanding of project performance. Second, proper levels of aggregation are required for the analysis of EPSoS. An important aspect of analysis of complex engineering projects is understanding the emergent properties of projects based on aggregation of dynamic behaviors and interactions. Emergent properties arise from interactions between different constituents in EPSoS and have significant impacts on project performance. Hence, an aggregation approach that can effectively assemble the dynamics and interdependencies at different levels of engineering projects and finally capture the emergent properties at the project level is needed. Third, the evolutionary nature of EPSoS requires a dynamic approach for analysis and assessment of project performance over time. Unlike the traditional project management frameworks, in which a detailed baseline plan is developed at the beginning of a project and stays static through the project life cycle, the EPSoS framework should be able to react to the changes in project goals, plans, structures, and outcomes. Fourth, the interdependencies in engineering projects through exchange of information and social interactions need to be considered in the analysis of EPSoS. EPSoS consist of both human and physical entities. The conventional approaches to analysis of project systems mainly focus on physical system exchanges. However, many of the interdependencies in EPSoS are actually developed through human interactions and information exchanges, especially when different sub-systems are geographically distributed. In addition, the interactions between human agents, in the context of project social networks, influence the dynamic behaviors in engineering projects. Thus, an appropriate framework for the analysis of EPSoS should be able to capture the interdependencies between social and technical elements of project systems.

2.3 Systems-of-Systems Framework of Complex Engineering Projects

Based on the requirements for the analysis of EPSoS, an EPSoS framework (Figure 2-1) is proposed in this paper as a methodological structure for the creation of tools and techniques for performance assessment and management in complex engineering projects. Two principles are used to develop the EPSoS framework: (1) base-level abstraction, and (2) multi-level aggregation.

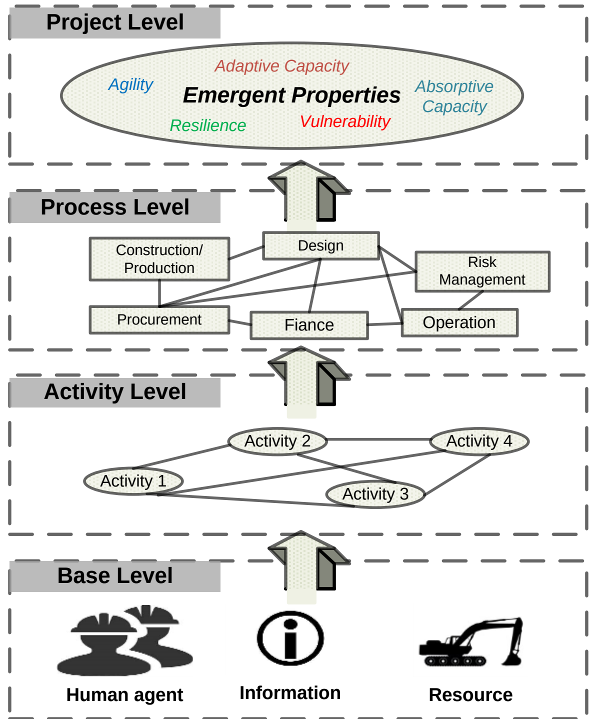


Figure 2-1 Engineering Project Systems-of-Systems Framework

2.3.1 Base-level abstraction

The first principle in the EPSoS framework is base-level abstraction. In order to capture the micro-behaviors and interdependencies of constituents in projects, engineering projects are abstracted at a base level in the proposed framework. At the base level, there are three types of basic entities: human agent, resource, and information. These three types of entities and their interdependencies are the basis for the activities and processes of any engineering project.

Human Agent: Human agents are autonomous entities who utilize information and resources to conduct different activities, including production work, information processing, and decision making in engineering projects. One human agent can undertake activities of one or multiple types. One human agent entity could be an individual, a crew, or a team. The dynamic behaviors of human agents are determined by their attributes, such as skill levels, risk attitudes, and attention allocation. For example, when a human agent is conducting production work, examples of important attributes may include skill type and skill level. The required skill type for a human agent in an engineering project could be the design skill for an engineer in an aerospace project, or the assembly skill for a carpenter in a construction project. Skill level of a human agent is related to the capability and experience of the agent. The skill type and skill level of a human agent will directly determine whether the human agent can successfully implement the work and the corresponding productivity. When a human agent is conducting information-processing activities, one of the most important attributes is response time, which determines how long it takes for them to process and pass the information to the right persons. When a human agent makes decisions in engineering projects, one of the most significant attributes is risk attitude. Human agents can have different risk attitudes (e.g., risk-seeking, risk-averse, or risk-neutral) based on their acceptable level for uncertain outcomes (Weber, Blais, & Betz, 2002). A risk-seeking human agent is more likely to make decisions that have greater likelihoods of gains, even though the uncertainty of the outcomes is also greater. On the other hand, a risk-averse human agent tends to make decisions that reduce the likelihood of losses. For example, an inspector in an engineering project is conducting material inspections and has the autonomy to decide the number of samples to a certain extent. A risk-seeking inspector may choose the number of inspection samples according to the minimum requirement by specifications to save time and effort, while a risk-averse inspector may select a larger number of samples to be more certain about the results.

The abstraction of base-level human agents in the proposed EPSoS framework has two distinguishing features. First, the attributes considered for human agents are based on the activities they undertake instead of their positions. In other words, the decision-making authority is not limited to the top levels in a hierarchical structure used in the traditional project management frameworks. The autonomy of human agents, no matter whether they are project managers or first-line workers, is taken into consideration based on actual situations in projects. Second, in the proposed EPSoS framework, attributes of human agents are studied as dynamic variables that could change over time under the influence of various factors (e.g., knowledge transfer, specialty training, or changes in project environment). For instance, the skill level of a worker may improve over time due to the learning effect. The risk attitude of a project manager may change due to fluctuations in the economic environment. The attributes of human agents directly determine their dynamic behaviors under different circumstances. Investigating the attributes of human agents using the proposed framework enables a better understanding of the outcomes of the activities they undertake, and furthermore, the project performance as an integrative outcome.

Resource: Resource is another type of base-level entity. In EPSoS, human agents use resources to facilitate completion of activities assigned to them. The main types of resources in EPSoS are material and equipment. There are different types of materials in engineering projects, such as concrete in construction projects or high strength carbon steel in aerospace projects. Important attributes of materials considered in the EPSoS framework include quantity, quality, and unit cost. Similarly, there are various types of equipment used in engineering projects, such as software programs used in the design process of engineering projects, manufacturing machines used in the production process, and vehicles used for delivery of raw materials in the procurement process. Examples of important attributes of equipment considered in the proposed framework include productivity and unit cost. One of the important factors causing variations in performance of engineering projects is resource uncertainty (e.g., uncertainty in material quality or equipment productivity). In previous studies, the uncertainty of resources was considered as an independent risk factor. However, no mechanism has been developed to investigate how the resource uncertainty affects the information flow and dynamic behaviors of human agents, which ultimately affect performance in projects. In the EPSoS framework, the analysis of resources at the base level considers the interdependencies between the resource and information flow, as well as behaviors of human agents. For example, in a construction project, the uncertainty related to the quality of concrete delivered to the jobsite not only directly affects the quality of the project, but also has other indirect influences on the project by affecting the behaviors of human agents. For instance, if different batches of concrete are tested randomly, a higher level of uncertainty (i.e., variation) in the concrete quality among different batches may cause the inspector to increase the frequency of sampling and testing, thus affecting the cost and schedule performance of the project.

Information: Information is critical in EPSoS since many interdependencies in projects exist because of information exchange or sharing. However, the attributes of information and their impacts on project performance were underrated in previous studies. In the proposed framework, at the base level of EPSoS, two types of information are abstracted: existing information and emergent information. Existing information is information that can be obtained and utilized at the beginning of the project. Project permits, industry specifications, and environmental regulations are examples of existing information in engineering projects. Examples of important attributes of existing information include availability, completeness, accuracy and reliability. Different from existing information, emergent information is generated during a project. Examples of emergent information include the decisions made by human agents, outcomes of activities, and occurrences of unexpected events. For emergent information, there are other significant attributes besides the attributes of existing information. For example, recentness is an example of important attributes of emergent information. Recentness represents how recently a piece of information is generated or updated. In a dynamic environment where information constantly emerges and changes, a more recent piece of information is more likely to represent the current state of the environment and thus is more reliable (Fullam & Barber, 2005). Information is the key for many of the interdependencies in engineering projects. Different attributes of information lead to different decisions and actions of human agents, thus greatly affecting the ultimate performance outcomes of engineering projects. For example, the change in the requirements of a client/user is a piece of emergent information in engineering projects. A timely, complete, and accurate piece of information regarding the change in client/user requirements helps stakeholders make rational decisions and implement adaptive actions in projects. Thus, investigating the attributes of information at the base level of engineering projects can provide a better insight into performance outcomes.

2.3.2 Multi-level aggregation

The second principle for developing the EPSoS framework is multi-level aggregation. Different levels exist in SoS. Higher levels of SoS are collections of constituents and interdependencies at lower levels (DeLaurentis & Crossley, 2005). In the EPSoS framework, there are four levels of analysis: base level, activity level, process level, and project level (Table 2-1).

Table 2-1 Four Levels in EPSoS Framework

Name	Description
Base Level	Base level entities of human agents, resources, and information
Activity Level	Each activity is a collection of base-level entities
Process Level	Each process is a collections of activities
Project Level	A project is a collections of processes

Base level is the level where human agents, resources, and information, as well as the attributes of all three, are abstracted in order to adequately capture the micro-behaviors in EPSoS. At the activity level, each activity is a collection of base-level entities (i.e., human agents, resources, information) and their interdependencies (e.g., who uses what resources for a certain activity, who uses what information for a certain activity, what information is needed for using what resource in a certain activity). Activities in engineering projects include production work (e.g., designing the project/product, assembling parts), information processing (e.g., obtaining material standards from specifications, reporting unforeseen conditions) and decision making (e.g., making decisions on the selection of equipment, making decisions on whether to acquire more workforce to accelerate the project). Different activities are then aggregated at the process level, where each process is a collection of activities and their interdependencies (e.g., the outcome of one activity provides required information or semi-finished products for another activity). Different processes (i.e., sub-systems) in engineering projects (e.g., design sub-system, construction/production sub-system, and risk management sub-system) can be analyzed and assessed at the process level in the proposed framework. Finally, different processes in an engineering project are aggregated at the project level. At the project level, the interdependencies and interactions between different processes give rise to emergent properties (e.g., absorptive capacity, adaptive capacity, vulnerability, and resilience) of an engineering project. Emergent properties, as integrative attributes, determine the macro-behaviors of an engineering project under different scenarios. The four-level analysis facilitates a bottom-up approach for performance assessment from the base level to the project level. By the multi-level aggregation, the performance at each level of projects (e.g., activity performance, process performance, and project performance) can be better assessed based on the abstraction of entities at the base level. The bottom-up aggregation structure of EPSoS is dynamic due to the existence of interdependencies and feedbacks. For example, an information entity at the base level could be the outcome of an activity, and this information entity might in turn affect the activity. Thus, the multi-level aggregation structure of EPSoS needs to be constantly monitored and modified according to the dynamic changes.

Based on these two principles (i.e., base-level abstraction and multi-level aggregation), the proposed framework fulfills the requirements for analysis of EPSoS and can potentially address the limitations in traditional performance assessment and project management approaches. First, engineering projects are abstracted at a base level, which facilitates capturing the micro-behaviors and interdependencies in engineering projects. Second, a four-level aggregation facilitates a bottom-up assessment of project performance.

Emergent properties can be captured at the project level as integrative attributes of projects. Third, the proposed framework has a dynamic view of engineering projects, which helps to take the impacts of risks and uncertainties in projects into consideration. There are various sources of risks and uncertainties both in project systems and their operating environments. In the EPSoS framework, these risks and uncertainties can be addressed either by considering the randomness and dynamic changes in base-level entities' attributes or by considering the dynamic interdependencies in the aggregation structures of project systems. Finally, through interdependencies and interactions between base-level entities of human agents and information, the social aspects of EPSoS are highlighted in the proposed framework.

2.4 Application Example

The proposed EPSoS framework provides new opportunities for studying and analyzing engineering projects. One of these opportunities is to investigate project performance based on different attributes of base-level entities. In this paper, the analysis of a complex construction project is used to demonstrate this application. Using the EPSoS framework, various entities and their attributes were abstracted and used in a computational model. Simulation experiments were conducted to investigate the impacts of attributes of base-level entities on project performance by using the computational model. The findings highlight the capability of the proposed framework in facilitating a bottom-up assessment of performance in engineering projects.

2.4.1 Case description

The numerical case is related to a 1600-meter long tunnel construction project. The information of the case project was mostly obtained from Ioannou and Martinez (Ioannou & Martinez, 1996), who used the discrete event simulation method to model the construction process of the tunnel. The tunnel is constructed using the New Austrian Tunneling Method (NATM). Compared to the conventional tunneling method, which uses the suspected worst rock condition for design, the NATM enables cost savings by adjusting the initial design during the construction phase.

The ground conditions vary along the length of the tunnel and are classified into three categories: Good, Medium, and Poor. The ground condition persists for at least 100 meters. At the beginning of the project, only the ground condition of the first 100 meters is known. The project is conducted in sections. Each section has a step length of 100 meters, 200 meters, or 400 meters. For each section, the designer makes a decision about the excavation rate and type of support based on the ground condition discovered at the end point of the previous section, the state transition probability matrix, and its risk attitude. The state transition probability matrix (Table 2-2) is a piece of existing information obtained from historical data (Ioannou & Martinez, 1996). This information can be used to predict the ground condition of the next section. For example, if the ground condition at the end point of the previous section is identified to be Good, then according to historical data there is 60% probability for the ground condition of the next section to be also Good, 25% probability of being Medium, and only 15% probability of being Poor. The designer then uses this prediction to adopt the appropriate excavation rate and type of support. Based on the prospect theory (Kahneman & Tversky, 1979), designers with different risk attitudes will make different design decisions (Table 2-3). Using a better ground condition for design could save time and cost in construction, although it also brings higher possibilities of quality deficiencies in the project. A risk-seeking designer tends to be more optimistic on the ground conditions. As shown in Table 2-3, if the ground condition is predicted to be in the Medium category, there is 60% likelihood that a risk-seeking designer chooses the excavation rate and type of support appropriate for the Medium ground condition. There is still 40% likelihood that the designer selects excavation rate and type of support appropriate for the Good ground condition. A risk-averse designer has the opposite attitude in which more conservative decisions about excavation rate and type of support are made based on the predicted ground condition. A risk-neutral designer uses exactly the predicted ground condition as the basis for making decisions. After the designer makes the design decision, the workers start constructing that section. There are two major activities considered in the construction process: excavation and support placement. The productivity and corresponding cost rate related to these two activities are different, based on different design decisions (Table 2-4) (Ioannou & Martinez, 1996).

After the construction of one section is finished, the workers collect rock samples and test the actual ground condition at the end point of that section. This ground condition is a piece of emergent information. The workers report this information to the designer and the designer will use it for designing the following section. The workers also report this information to the risk manager. However, the reporting to the risk manager is conducted randomly. The risk manager can use this information to assess the design quality and determine the step length for the following section accordingly. The risk manager compares the reported ground condition with the excavation rate and type of support used for the finished section. If the excavation rate and type of support used in the section doesn't match the reported ground condition, the risk manager identifies it either as an "under-designed" or "over-designed" section. In an "under-designed" section, the designer's decision on the excavation rate and type of support cannot meet the requirement of the reported ground condition (de Bruijn & Leijten, 2008). For example, if the ground condition at the end point of a section is reported as Medium, while the excavation rate and type of support decided by the designer are appropriate for the Good ground condition, it is an "under-designed" section. An "Over-designed" section is an opposite case in which the decision made by the designer exceeds the requirement of the reported ground condition (de Bruijn & Leijten, 2008). In either case, the risk manager will make the decision of decreasing the step length for the next section (e.g., from 400 meters to 200 meters) to reduce the risks as the designer will have more chances to adjust the design according to reported ground conditions. In contrast, if the excavation rate and type of support used match with the reported ground condition, the risk manager considers this section as designed and built appropriately and increases the step length for the next section (e.g., from 100 meters to 200 meters). The decision related to the step length made by the risk manager is reported to the designer and workers and the next round for design and construction continues. At the end of the project, the overall design quality of the project is assessed by two indicators: the under-designed percentage (i.e., the ratio of the total length of under-designed sections to the total length of the tunnel) and the over-designed percentage (i.e., the ratio of the total length of over-designed sections to the total length of the tunnel). For both indicators, the higher the value of the indicators, the worse the design quality. However, the ground condition may vary in one section. Using the ground condition discovered at the end point of a section to represent the whole section doesn't provide the subjective results of under-designed and over-designed instances. So differences exist between the actual and perceived under-designed percentage as well as over-designed percentage.

Table 2-2 State Transition Probability Matrix (Ioannou & Martinez, 1996)

From Ground Category	To Ground Category		
	Good	Medium	Poor
Good	0.60	0.25	0.15
Medium	0.10	0.80	0.10
Poor	0.05	0.20	0.75

Table 2-3 Decision Probability Matrix of Designers with Different Risk Attitudes

Predicted Ground Condition Category	Actual Design Decision (risk-seeking/risk-neutral/risk-averse)		
	Good	Medium	Poor
Good	1 /1 /0.6	0/0/0.3	0/0/0.1
Medium	0.4/0/0	0.6/1/0.6	0/0/0.4
Poor	0.1/0/0	0.3/0/0	0.6/1/1

Table 2-4 Productivity and Cost Rate (Ioannou & Martinez, 1996)

Productivity and cost	Design Decision		
	Good	Medium	Poor
Excavation Rate (meter/hr)	Triangular (0.37,0.38,0.43)	Triangular (0.32,0.33,0.40)	Triangular (0.13,0.17,0.32)
Excavator Operating Cost ($/hr)	2019	1760	1750
Support Placement Rate (meter/hr)	Uniform (0.55,0.65)	Uniform (0.37,0.47)	Uniform (0.15,0.30)
Support Cost ($/meter)	940	1160	1350

2.4.2 Implementation of EPSoS framework

This tunneling project involves multiple dynamic and complex processes. A high level of interdependence exists between the base-level agents, resources and information. The EPSoS framework was used for analysis of this complex project. First, the project was abstracted at the base-level. Table 2-5 summarizes the human agents, resources, and information in the tunneling project as base-level entities. The important attributes of the base-level entities considered in this case project (e.g., risk attitude of the designer, recentness of the ground condition) were captured.

Table 2-5 Base-level Entities and Attributes in the Case Project

Base-level Entities	Name	Attributes
Human Agent	Designer	Risk attitude
	Workers	Productivity
	Risk Manager	-
Resource	Excavator	Productivity; Unit cost
	Support	Unit cost
Information	State transition probability matrix	Availability
	Ground condition prediction	-
	Design decision	-
	Reported ground condition	Recentness
	Step length	-

Then, the second principle of the EPSoS framework, multi-level aggregation, was applied in the tunneling project (Figure 2-2). Using the EPSoS framework, the level of aggregation can be made at activity, process and project levels, based on the abstraction of base-level entities. At the activity level, each activity in the tunneling project can be represented as a network of human agents, resources, and information. For example, the network of the excavation activity consists of human agents (i.e., workers), resource (i.e., excavator), and information (i.e., design decision, step length, and ground condition report). In this activity, workers receive information related to design decision and possible step length change from the designer and risk manager, respectively. Then, the workers excavate using the equipment (i.e., excavator) with the productivity rate determined by the design decision throughout the step length. Finally, they report the ground condition discovered at the end point of the constructed section. In the tunneling project, there are many other activities, such as support placement in the construction process, making the design decision in the design process, and changing the step length in the risk management process. Similar activity networks can be developed for all the activities in the design, construction, and risk management processes. At the process level, different processes in the tunneling project can be represented as networks of activities. For example, the construction process in the case project consists of two activities (i.e., excavation and support placement). Each activity is an aggregation of base-level entities and interactions. Since the two activities share the same human agent entity (i.e., workers), a sequential interdependency exists between the two activities in the construction process. Finally, different processes (i.e., design, construction, and risk management processes) are aggregated at the project level. In the tunneling project, information exchanges make up most of the interdependencies between different processes. For example, risk management process needs the reported ground condition from the construction process for deciding the step length. After the decision for step length is made, this emergent information will be sent to the construction process for the workers to use in construction.

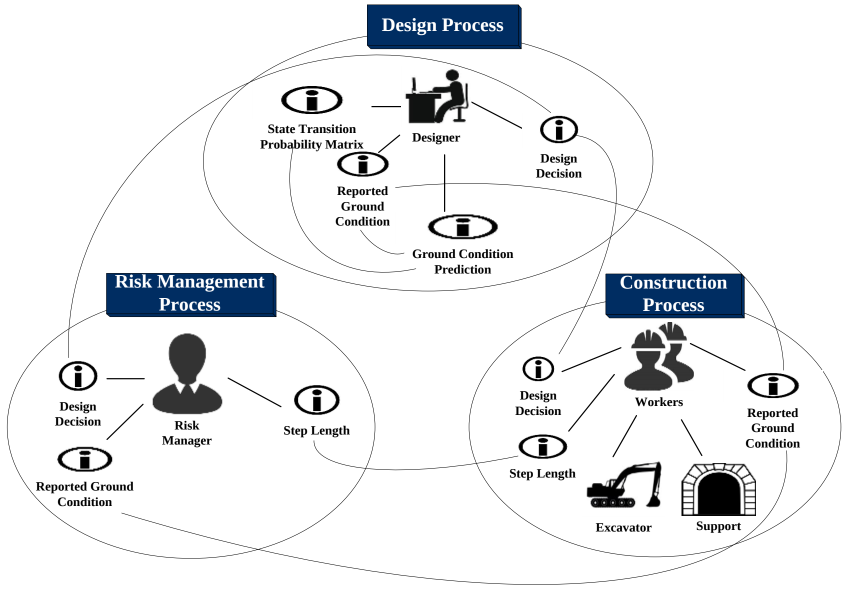


Figure 2-2 Aggregation of Base-level Entities in the Tunneling Project

2.4.3 Bottom-up simulation

Based on the conceptualization of the tunneling project using the EPSoS framework, an agent-based model was developed to perform a bottom-up simulation analysis of the project. Agent-based modeling is a widely used modeling approach for micro-simulation in systems with adaptive and dynamic components (Zhu & Mostafavi, 2014b; Zhu, Mostafavi, & Ahmad, 2014; Mostafavi, Abraham, & DeLaurentis, 2014; Mostafavi et al., 2015). Figure 2-3 and Figure 2-4 demonstrate the class and sequence diagrams related to the computational model using a Unified Modeling Language (UML) protocol. As shown in Figure 2-3, the class diagram defines the static relationships in the model. Four classes of objects were identified as designer, workers, risk manager, and main class. The main class has a composition relationship with the other agent classes. All the agents and their actions were embedded in the main class. In each agent class, attributes and operations were defined based on the base-level abstraction using the EPSoS framework. For example, for the designer agent, risk attitude is one of the attributes. Another attribute is “availability of historical data”. The historical data refers to the “state transition probability” as one piece of existing information abstracted at the base level of the tunneling project. Both attributes of the designer affect the designer’s operation of design. Figure 2-4 shows the sequence of events in the agent-based model by focusing on the message exchanges between agent classes. The sequence diagram was developed based on the interdependencies between base-level entities in the tunneling project, as identified using the EPSoS framework. For example, workers start working after receiving the design information sent by designer. After workers finish the construction work for a section, a message about the ground condition discovered at the end point will be sent to designer and risk manager to trigger their operations.

The computational model was developed using AnyLogic 7.0.0. Using the computational model, simulation experiments were conducted to gain a better understanding of project performance using a bottom-up approach. During the simulation experiments, different scenarios were created by changing the values of the attributes of base-level entities. Under each scenario, multiple runs of Monte-Carlo simulation experimentations were conducted to obtain project performance, such as time, cost and design quality. The randomness of the simulation experiments was originated from probability distributions of input parameters in the model (e.g., decision probability matrix, triangle distribution of excavation rate). The random numbers across multiple runs were obtained using a Linear Congruential Generator in AnyLogic (Borshchev, 2013).

Performance outcomes under different simulation scenarios were then compared to quantify the impacts of the attributes of base-level entities on project performance.

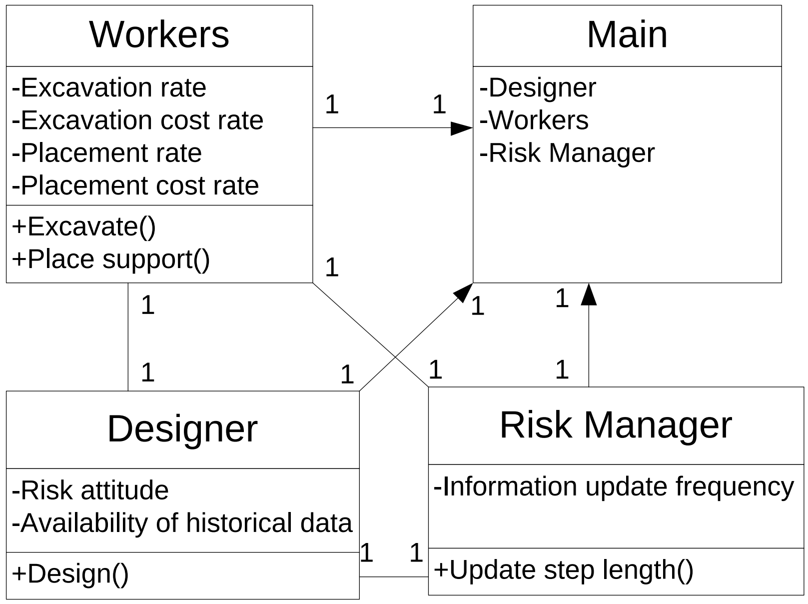


Figure 2-3 Class Diagram of the Agent-based Model

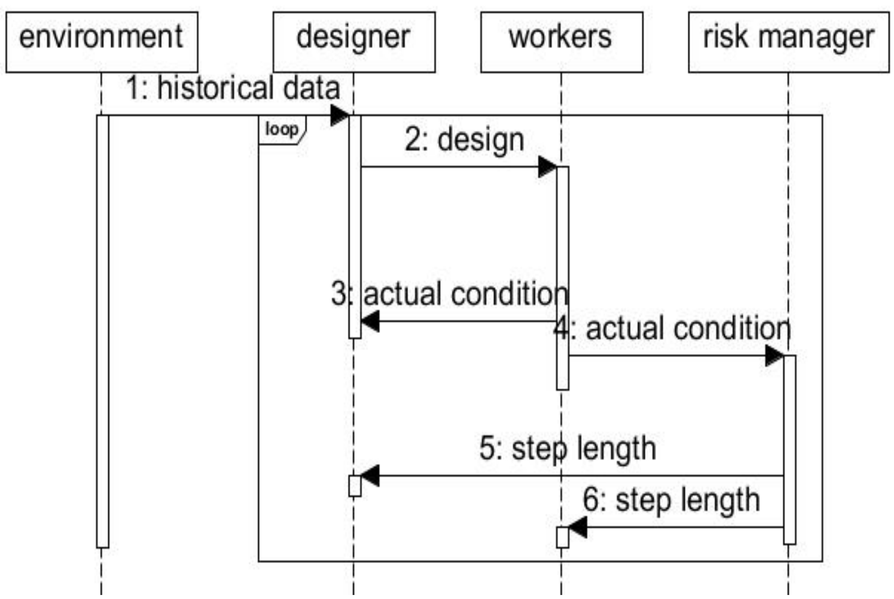


Figure 2-4 Sequence Diagram of the Agent-based Model

2.4.4 Results

Three sets of simulation experiments related to the risk attitude of human agents, the availability of existing information, and the recentness of emergent information are presented as follows.

(1) Impacts of human agents

In the first set of simulation experiments, three scenarios related to different risk attitudes of designer (i.e., risk-seeking, risk-neutral, and risk-averse) were developed. 100 runs of Monte Carlo simulation experiments were conducted under each of the scenarios using the agent-based model. The number of runs for Monte-Carlo simulation was determined using the methodology developed by Byrne (2013). First, 20 simulation runs were conducted to estimate the coefficient of variation of different sets of simulation results. Then, based on a table of minimum number of runs suggested by Byrne (2013), it was determined that 100 runs were required. The simulation results show that the risk attitude of human agents affects the performance of the tunneling project in multiple ways. First, a risk-seeking designer improves project time and cost. Figure 2-5 and Figure 2-6 show the probability distributions of simulation results of project time and cost under the three scenarios. As shown in Figure 2-5, if the risk attitude of the designer is risk-averse, the average total project time is 482.6 days. The mean value pertaining to the project time over multiple runs decreases by 15.58% if the risk attitude of the designer is risk-neutral, and by 25.45% if the risk attitude of the designer is risk-seeking. Similarly, Figure 2-6 shows the impact of the risk attitude of the designer on the project cost. The mean value pertaining to the project cost is $13.04 million if the risk-attitude of the designer is risk-averse. The mean value of project cost decreases by 12.65% and 18.02% if the risk attitude of the designer is risk-neutral and risk-seeking, respectively. An additional observation in both Figure 2-5 and Figure 2-6 is that the standard deviations pertaining to the project time and cost over multiple runs of simulation experiments are larger under the scenario when the risk attitude of the designer is risk-averse. This result implies a greater level of uncertainty on project time and cost when the risk attitude of the designer is risk-averse.

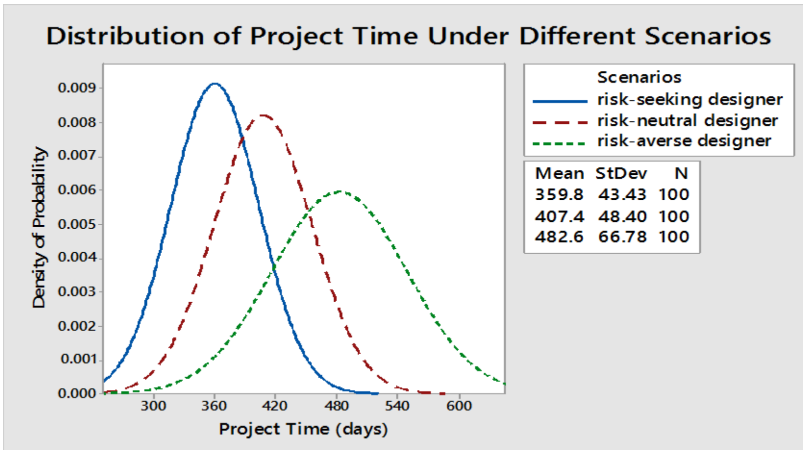


Figure 2-5 Project Time under Scenarios Related to Human Agents

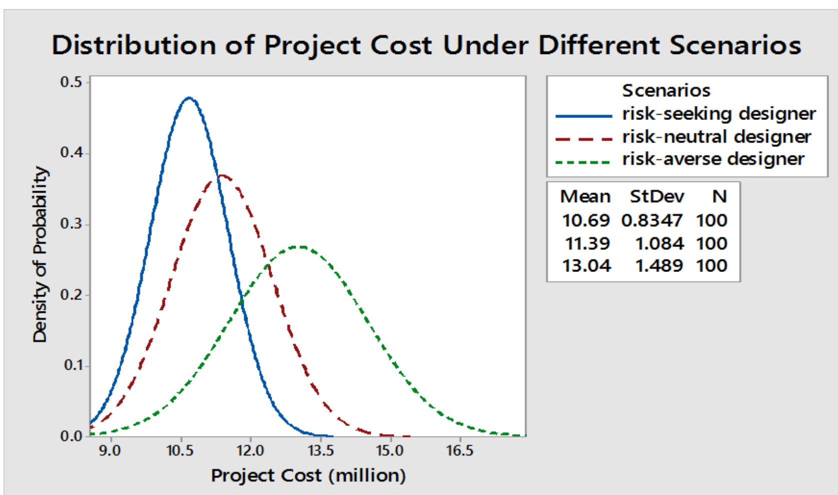


Figure 2-6 Project Cost under Scenarios Related to Human Agents

Besides project time and cost, designers with different risk attitudes also affect the performance outcomes in terms of design quality. Figure 2-7 shows the results related to both under-designed and over-designed percentages under different simulation scenarios. As shown in Figure 2-7, when the risk attitude of the designer is risk-seeking, the mean value of the under-designed percentage is 43.38%. It means that out of 1600 meters, it is perceived that around 694 meters were constructed below the standard requirement. The value of the under-designed percentage decreases under the scenarios when the risk-attitude of the designers are risk-neutral or risk-averse. On the contrary, the mean value of over-designed percentage is the highest under the scenario when the risk-attitude of the designer is risk-averse. The simulation results show that a risk-seeking designer leads to a greater under-designed percentage, and a risk-averse designer leads to a greater over-designed percentage in the tunneling project.

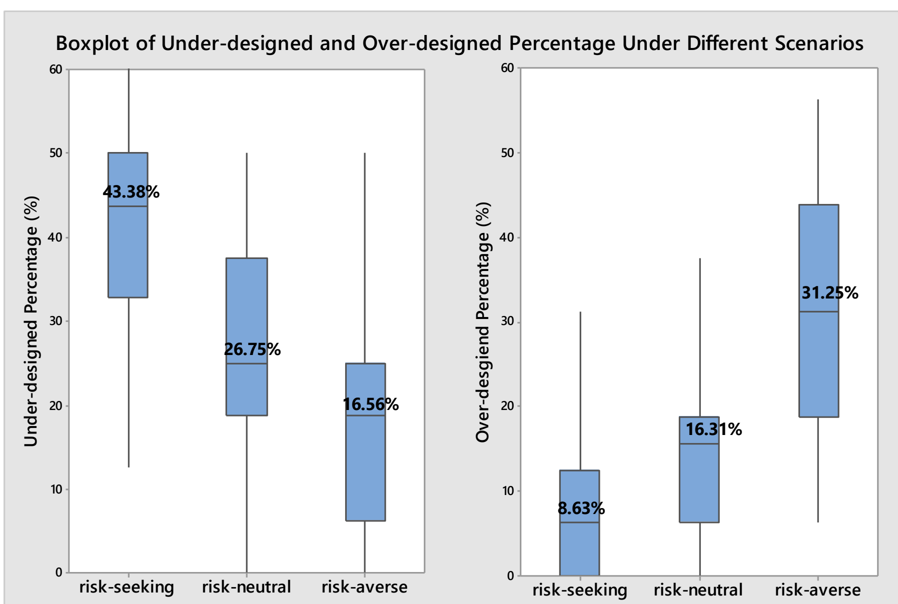


Figure 2-7 Under-designed Percentage and Over-designed Percentage under Scenarios Related to Human Agents

These findings show the varying effects that the attributes of base-level human agents could have on the performance measures quantitatively. Based on the findings, selection of a risk-seeking designer can improve the performance of the project with respect to time, cost, and design quality related to overdesign measures. In contrast, selection of a risk-seeking designer can exacerbate the design quality in terms of under-designed situations. Project managers and decision makers can use the results of this set of simulation experiments to select the most appropriate designer based on their priorities. In this numerical example, only the direct project time and cost related to excavation and support installation were considered. However, under-designed situations may lead to safety incidents. If safety incidents happen, more time and money will need to be spent in fixing the incidents and continuing with the work. Thus, selection of a risk-seeking designer might lead to worse project performance indicators related to time and cost if safety incidents are taken into consideration.

(2) Impacts of existing information.

The second set of simulation experiments explores the impacts of existing information at the base-level of EPSoS on project performance. One example of existing information in the tunneling project is the "state transition probability matrix", which is historical data related to the ground condition changes. During the simulation experiments, two scenarios were developed based on the availability of this information (i.e., "state transition probability matrix" is available for use, and "state transition probability matrix" is not available for use). 100 runs of Monte Carlo simulation experiments were conducted under the two scenarios. The simulation results show that the availability of static information also has significant impacts on project performance. Figure 2-8 and Figure 2-9 demonstrate the probability distributions pertaining to the time and cost performance measures under the two simulation scenarios. As shown in Figure 2-8, the mean value of project time is not affected significantly by the availability of the existing information. However, the standard deviation pertaining to the project time is greater if the existing information is not available. The availability of the existing information also affects the project cost. As shown in Figure 2-9, if the existing information is not available for the designer to use, the mean value of project cost increases slightly, as well as the standard deviation of project cost.

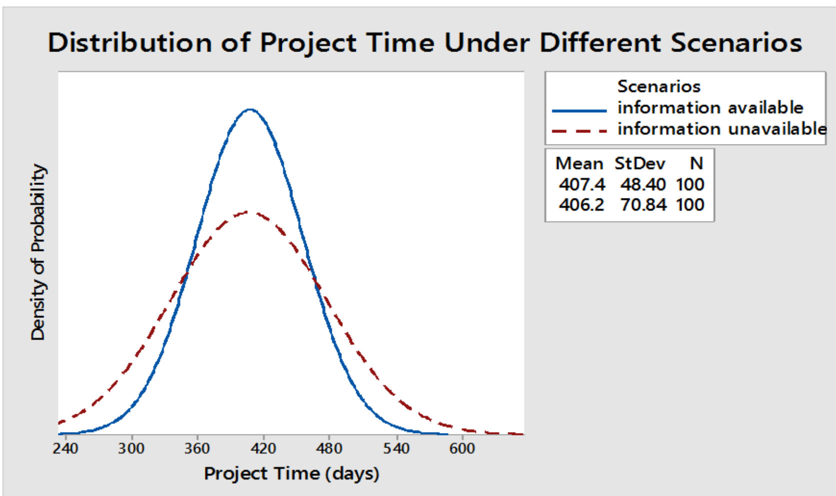


Figure 2-8 Project Time under Scenarios Related to Existing Information

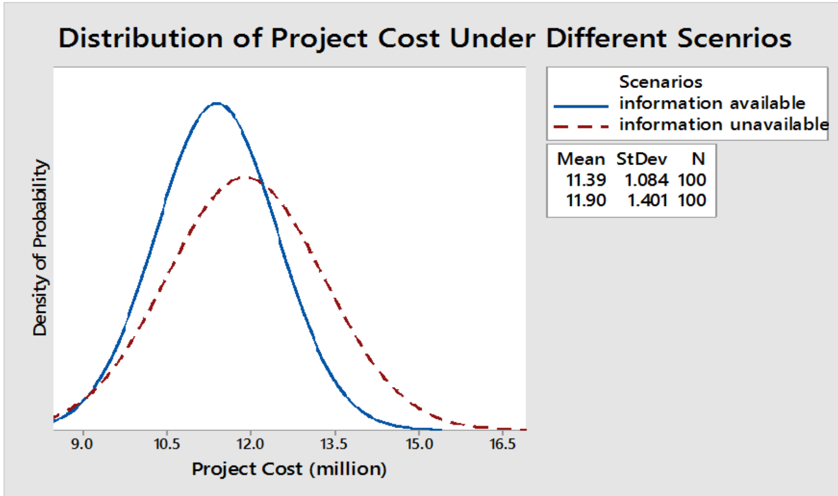


Figure 2-9 Project Cost under Scenarios Related to Existing Information

The availability of the existing information also affects the design quality in the tunneling project. As shown in Figure 2-10, when the existing information is available, the mean value pertaining to the under-designed percentage is 26.75%. The mean value pertaining to the under-designed percentage in the project increases to 36.75% when the information is not available. Similarly, according to Figure 2-11, the mean value pertaining to the over-designed percentage is 16.3% when the existing information is available, and increases to 21.44% if the information is not available. The results also show that the standard deviations of both indicators for design quality are greater under the scenario when the existing information is not available. These findings inform the importance of obtaining required information at the beginning of the project. In the tunneling project, the available of “state transition probability matrix” improves the project design quality, and reduces the uncertainty (measured by standard deviation of probability distributions) in project time and cost outcomes. The findings can be used to quantify the value of certain information in projects. Project managers and decision makers can then identify and prioritize the most important existing information, and allocation more resources to ensure the availability and accuracy of those information in project planning.

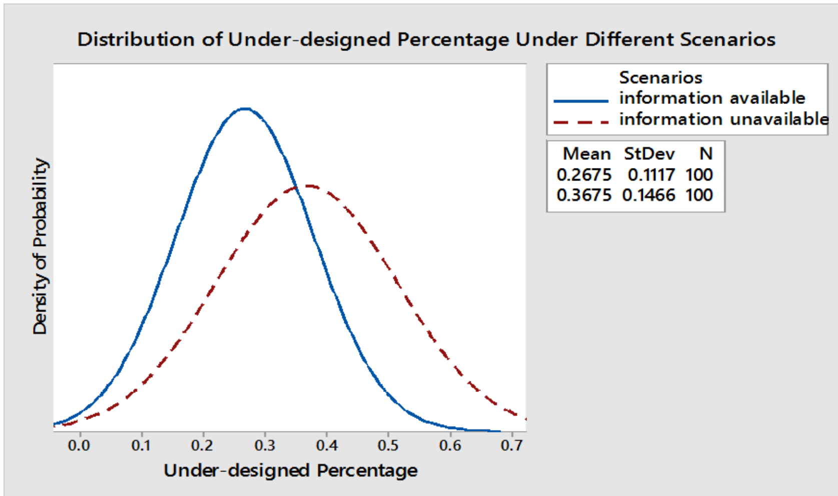


Figure 2-10 Under-designed Percentage under Scenarios Related to Existing Information

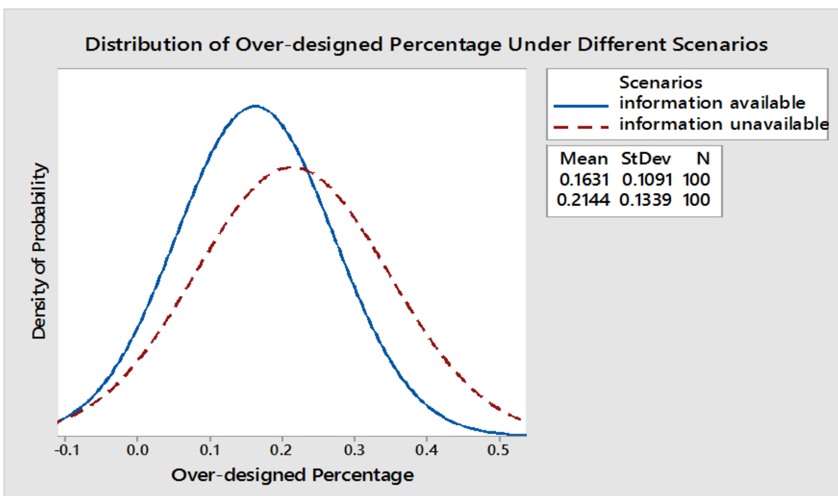


Figure 2-11 Over-designed Percentage under Scenarios Related to Existing Information

(3) Impacts of emergent information.

The third set of simulation experiments focus on the impacts of emergent information on project performance. One example of emergent information in the tunneling project is the ground condition reported to the risk manager during the project. The reported ground condition is the actual ground condition identified at the end point of each section. The risk manager uses this information to evaluate whether there is an under-designed or over-designed instance in the completed section, and changes the step length for the next section if necessary. Since the ground condition is reported to the risk manager randomly from time to time, recentness is an important attribute of the reported ground condition. The recentness of the reported ground condition in the tunneling project can be quantified as a continuous variable between 0 and 1. Having a recentness value equal to 0 means that the ground condition is not reported to the risk manager at the end of any section. Having a recentness value equal to 1 means that the ground condition is reported to the risk manager at the end of each section. Accordingly, if a recentness value is between 0 and 1, the ground condition is reported to the risk manager only at the end of some sections. A higher recentness value indicates that the ground condition is reported more frequently to the risk manager. During the simulation experiments, different scenarios were created by changing the value of recentness of reported ground condition. Accordingly, Monte-Carlo experiments were conducted under each scenario.

The results of the Monte-Carlo experimentations show no significant differences in time, cost, under-designed or over-designed percentage due to changes in recentness of the emergent information. However, the recentness of the emergent information affects the accuracy of the indicators of project design quality (i.e., under-designed percentage and over-designed percentage). The accuracy is assessed by the difference between the actual and perceived values pertaining to under-designed and over-designed percentages. The lower the difference, the more accurate the design quality indicators. This level of accuracy may not directly affect project performance indicators. However, it can affect a project by influencing the attributes of other base-level entities. For example, a designer may change his/her risk attitude from risk-averse to risk-seeking if the perceived design quality is good while in fact it is not. The change of risk attitude will then lead to changes in project time, cost, and design quality. As shown in Figure 2-12 and Figure 2-13, the differences between the actual and perceived values pertaining to under-designed percentage, as well as over-designed percentage, both decrease with increasing the recentness of the emergent information. In other words, the design quality indicators are more accurate when the information recentness increases. The results also show that the extent to which the recentness of the information affects the indicator accuracy varies based on the risk attitudes of the designer. As shown in Figure 2-12, the recentness of the emergent information has a more significant impact in reducing the difference between the actual and perceived under-designed percentage when the designer is a risk-seeker. Figure 2-13 shows that the recentness of the emergent information has a more significant impact in reducing the difference between the actual and perceived over-designed percentage when the risk attitude of the project designer is risk-averse. The findings in this set of simulation experiments can help project managers and decision makers to select the report or update frequency of emergent information based on the relevant requirement (e.g., performance indicator accuracy). Also, the simulation results highlight the synergy effect when considering different attributes of base-level components (e.g., risk attitudes of human agents and recentness of information) and their influences together.

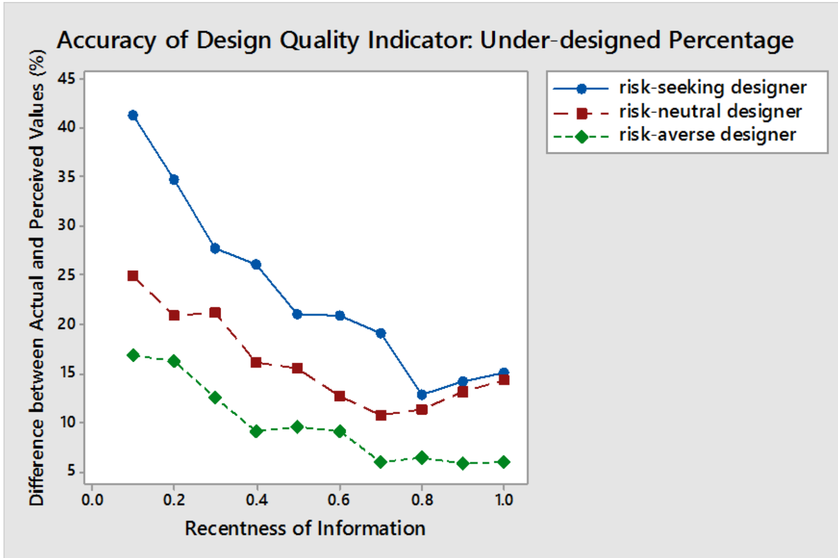


Figure 2-12 Differences between Actual and Perceived Under-designed Percentage under Scenarios Related to Emergent Information

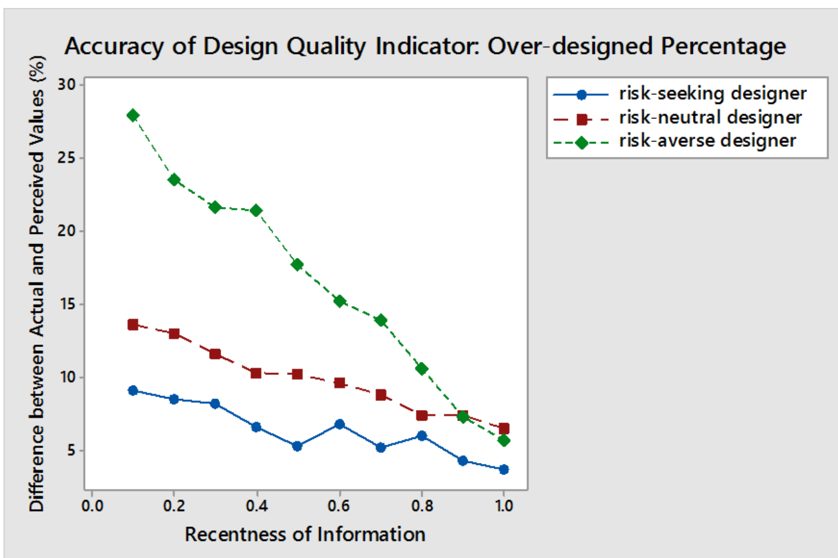


Figure 2-13 Differences between Actual and Perceived Over-designed Percentage under Scenarios Related to Emergent Information

2.4.5 Validation

The validity of the simulation model was tested using different validation techniques such as internal validation, extreme condition tests, and tracing techniques. For example, by using the tracing technique, the behaviors of specific agents (e.g., designer, workers) in the model were traced in different runs to determine if the model's logics were correct (Sargent, 2011). In addition, the simulation results were compared with the project performance indicators obtained in the reference study (Ioannou & Martinez, 1996). The project schedule obtained in different simulation scenarios in this study ranges from 359.8 days to 482.6 days, while the average project schedule obtained by Iounnou and Martinez (1996) was 378 days. The project total cost obtained in different simulation scenarios in this study ranges from $10.69M to $13.04M, while the average project cost obtained by Iounnou and Martinez (1996) was $10.84M. The comparison between the simulation results of this study and those from Iounnou and Martinez (1996) shows the validity of the simulation model results.

2.4.6 Discussion

The case study related to the tunneling project is one application example of the proposed EPSoS framework. In this demonstration of application, the proposed EPSoS framework enabled a formalized approach for abstraction of base-level entities and their interactions; these entities and interactions were then modeled using an agent-based model. The simulation results show the capability of the bottom-up analysis in capturing the impacts of different attributes of base-level entities on project performance. In this study, the impacts of risk attitudes of human agents, availability of existing information, and recentness of emergent information on project time, cost, and design quality were quantified using different simulation scenarios. In future studies, the impacts of other attributes of base-level entities (e.g., accuracy of existing information, quality of material) can be investigated using the same approach. Compared to the traditional approaches, the bottom-up performance assessment based on a SoS analysis provides additional insights on project performance and helps decision-makers to better predict and manage project performance (Table 2-6).

Table 2-6 Capabilities of EPSoS Framework

Limitations of traditional project management frameworks	Capability of EPSoS framework
Lack of consideration of autonomy of constituents in projects	Using the EPSoS framework, decision-making capability of both the designer and risk manager were considered
Lack of consideration of the impacts of micro-behaviors on project performance	Using the EPSoS framework, micro-behaviors such as ground condition reporting were considered
Lack of consideration of interdependencies	Using the EPSoS framework, interdependencies between entities across different levels were considered
Lack of consideration of changes and evolutions in projects	Using the EPSoS framework, project changes and evolutions due to the uncertain ground condition were considered

2.5 Conclusions

The existing uncertainty, complexity, resource constraints, and market demands call for a paradigm shift in the performance assessment and management of engineering projects (Zhu & Mostafavi, 2014c). This paper presents a SoS framework which provides an innovative methodological structure for analysis of complex engineering projects. The proposed EPSoS framework is different from traditional performance assessment and management frameworks in several aspects (Table 2-7).

Table 2-7 EPSoS Framework and Traditional Project Management Frameworks

	Traditional PM Framework	EPSoS Framework
Level of abstraction	Process and activity levels	Base level
Approach	Top-down	Bottom-up
Focus	Stand-alone factors in single process of activity	Integrative behaviors based on interdependencies

Based on these differences, the SoS framework facilitates considering dynamic behaviors, uncertainty, and interdependencies between constituents in engineering projects by employing two fundamental principles: base-level abstraction and multi-level aggregation. The proposed EPSoS framework provides new opportunities for studying and analyzing engineering projects. For instance, the numerical example of the tunneling project highlights the capability of the proposed EPSoS framework in abstraction of engineering projects at the base level and assessment of the impacts of attributes and micro-behaviors of three types of base-level entities (i.e., human agents, resources, and information) on project performance. In other research conducted by the authors, the EPSoS framework can enable investigating emergent properties such as project vulnerability based on the abstraction of interdependencies captured using the EPSoS framework (Zhu & Mostafavi, 2015a; Zhu & Mostafavi, 2015b).

As a novel framework for performance assessment in engineering projects, the EPSoS framework brings both scientific and practical contributions. In terms of scientific contributions, the EPSoS framework provides a new lens for assessment of engineering projects. The proposed EPSoS framework provides a formalized approach for abstraction of base-level entities and their interactions in order to better understand various important phenomena. Through the use of the proposed EPSoS framework, different modeling and analytical tools and methods, such as agent-based modeling and system dynamics, can be better implemented in studying engineering projects. Future studies can use the EPSoS framework as a guide in the creation of integrated theories and methodologies in performance assessment and management. For example, despite the investigation of the impacts of different base-level entities' attributes, the proposed framework can also be used in future studies to evaluate the effectiveness of different strategies in influencing the constituent parts of EPSoS. The proposed framework also contributes to the body of practice. Practitioners can better plan and manage engineering projects using the EPSoS framework in complex and uncertain environments. By using the EPSoS framework as an analysis and planning tool, practitioners can make better decisions on selection of base-level entities in engineering projects during the pre-planning phase. Also, practitioners can better forecast and control project performance by monitoring the dynamic interdependencies and interactions in project systems. These research findings will ultimately facilitate a paradigm shift towards proactive performance assessment and management in complex engineering projects.

The implementation of the proposed EPSoS framework would be most beneficial in studying large complex engineering projects where the significant factors and their influencing mechanisms on project performance remain unknown. New knowledge and better understanding of complex phenomena in engineering projects can be obtained through conducting bottom-up analyses. However, implementation of the EPSoS framework in large complex projects requires the capability to identify the relevant base-level entities, as well as their attributes and interdependencies. The computational complexity increases with the increase in the number of base-level entities and attributes abstracted and modeled. Future studies will evaluate the scalability of the framework and sensitivity of various parameters in projects to better examine the implementation of the framework in different contexts and for different objectives.

3. DISCOVERING COMPLEXITY AND EMERGENT PROPERTIES IN PROJECT SYSTEMS: A NEW APPROACH TO UNDERSTAND PROJECT PERFORMANCE

The objective of this chapter is to propose and evaluate an integrated performance assessment framework based on consideration of complexity and emergent properties in project systems. The proposed Complexity and Emergent Property Congruence (CEPC) framework provides a novel approach to understand and assess project performance in complex construction projects. The fundamental premise of the proposed framework is that a greater level of congruence between project emergent properties and complexity can potentially increase the possibility of achieving performance goals in construction projects. This study identified two dimensions of project complexity (i.e., detail and dynamic complexity) and three dimensions of project emergent properties (i.e., absorptive, adaptive, and restorative capacities), which are related to a project's ability to cope with complexity. Information collected from nineteen interviews with experienced construction project managers were transcribed, coded, and analyzed in order to verify the existence of different dimensions of complexity and emergent properties in projects. In addition, various significant contributing factors to different dimensions of project complexity and emergent properties were identified. The results highlight the significance of the CEPC framework in understanding complexity and emergent properties in project systems and providing an integrated theoretical lens for project performance assessment.

3.1 Introduction

Over the past few decades, different project management theories and methods have been created to improve performance in construction projects. Despite these efforts, construction projects still suffer from low efficiency. A study conducted by the Construction Industry Institute (CII) shows that only 5.4% of the 975 construction projects studied met their planned performance objectives in terms of cost and schedule (Construction Industry Institute, 2012). One of the important obstacles in improving the efficiency of construction projects is that the existing performance assessment theories are incapable of capturing and dealing with the increasing complexity of modern construction projects. To address this knowledge gap, this study focuses on achieving a better understanding and assessment of project performance through investigation of a project's capability to cope with complexity.

To this end, this study adopts theoretical underpinnings from complex system science and organizational theory in order to propose an integrated framework for performance assessment, one based on investigation of emergent properties in complex construction project systems. In the proposed framework, performance of a construction project can be evaluated based on the extent of congruence between the project's emergent properties pertaining to its capability to cope with complexity and the level of project complexity. A greater level of congruence between project emergent properties and complexity can potentially increase the possibility of achieving performance goals in construction projects. A qualitative research method was used to verify the proposed framework and further investigate the different dimensions of project complexity (i.e., detail and dynamic complexity) and emergent properties (i.e., absorptive, adaptive and restorative capacity) in the context of construction project systems via semi-structured interviews with senior project managers.

The following sections are arranged as follows. First, the theoretical background of the proposed framework is presented. Second, different components of the proposed framework are introduced and explained. Third, the data collection and analysis process related to the interviews with senior project managers are demonstrated. Fourth, the data analysis results are presented. Finally, the significance of this research, its potential implications, and future research efforts are discussed.

3.2 Background

3.2.1 Traditional performance assessment approaches

Traditional approaches pertaining to performance assessment in construction projects are rooted in a reductionist perspective (Levitt, 2011; He, Jiang, Li, & Le, 2009). From the reductionist perspective, a construction project is simply an assemblage of various processes and activities, which are connected in order to perform the predefined baseline plan. In traditional studies related to performance assessment, the success or failure of construction projects were often investigated based on the attributes of individual processes, activities, or constituents in projects, such as financial conditions of owner, experience of contractors, project manager's competence, quality of site management and supervision, and availability of material and equipment (D. W. M. Chan & Kumaraswamy, 1996; A. P. C. Chan, Ho, & Tam, 2001; Iyer & Jha, 2005; Alzahrani & Emsley, 2013). The main limitation of this stream of studies is their deterministic and one-size-fits-all nature. The assumption underlying these studies is that certain attributes (so called critical success factors) guarantee success of a project regardless of the existing level of complexity. However, modern construction projects usually are large-scale systems operating in dynamic environments. Many modern construction projects are complex systems composed of multiple interrelated processes, activities, players, resources, and information (Zhu & Mostafavi, 2014c). Changes in one constituent of a project system can cause unforeseen changes in other constituents. The feedback processes and linkages between different constituents cause the project to evolve over time (Taylor & Ford, 2008). Hence, the behaviors and performance outcomes of construction projects are dynamic and unpredictable due to the complex interdependencies between various constituents in project systems. Traditional performance assessment approaches lack of consideration of the impacts of different levels of complexity on project systems, and thus, fail to capture the dynamics and unpredictability of project performance.

In another stream of studies, researchers have investigated different aspects of complexity and their impacts on project performance. Various factors (e.g., project size, uncertainties in scope, technological novelty of the project, diversity of tasks, and frequency and impacts of changes) contributing to project complexity were identified and their effects on project performance were studied (Williams, 1999; Bosch-Rekveldt, Jongkind, Mooi, Bakker, & Verbraeck, 2011; Giezen, 2012; Kardes, Ozturk, Cavusgil, & Cavusgil, 2013). Although this stream of research has emphasized the significance of complexity in assessment of project performance outcomes, it fails to consider ways a project copes with complexity. The majority of the existing studies in this stream of research investigate the level of complexity as an independent influencing factor affecting project performance. However, each project system has unique characteristics in terms of the ability to cope with complexity. The extent of the impacts of complexity on the performance of a project depends greatly on the ability of the project system to cope with complexity. Hence, outcomes of this stream of research may explain why a project fails due to complexity. But these studies do not provide insights regarding how to proactively design project systems that are capable of successfully operating in complex contexts.

3.2.2 Performance assessment based on contingency theory

The literature on contingency theory, as another avenue of research, provides a new perspective to understand and assess the performance of project systems. The fundamental premise of the contingency theory is that organizational effectiveness results from fitting organizational characteristics, such as its structure, to contingencies that reflect the situation of the organization (Donaldson, 2001). The use of contingency theory can provide a theoretical lens with which to investigate the performance of a construction project. In a construction project, the level of complexity can be viewed as contingency. Hence, the efficiency of a project is contingent on the congruence between the project's capability to cope with complexity (i.e., project characteristics) and the level of complexity (i.e., contingency factor). As shown in Figure 3-1, there are four possible conditions, based on the level of congruence that pertains to complexity in a project. In conditions A and C, a project's capability to cope with complexity is congruent with its level of complexity. Hence, both conditions have greater likelihoods of achieving project performance goals. On the contrary, an incongruent relationship between a project's capability to cope with complexity and the existing level of complexity may lead to undesirable outcomes in a project. For example, in condition B, a project's capability is insufficient to cope with the existing level of complexity, and thus the project may have a lower chance of achieving performance goals. In condition D, a project has a higher level of capability to cope with complexity than actually required, and thus it might not be cost-effective.

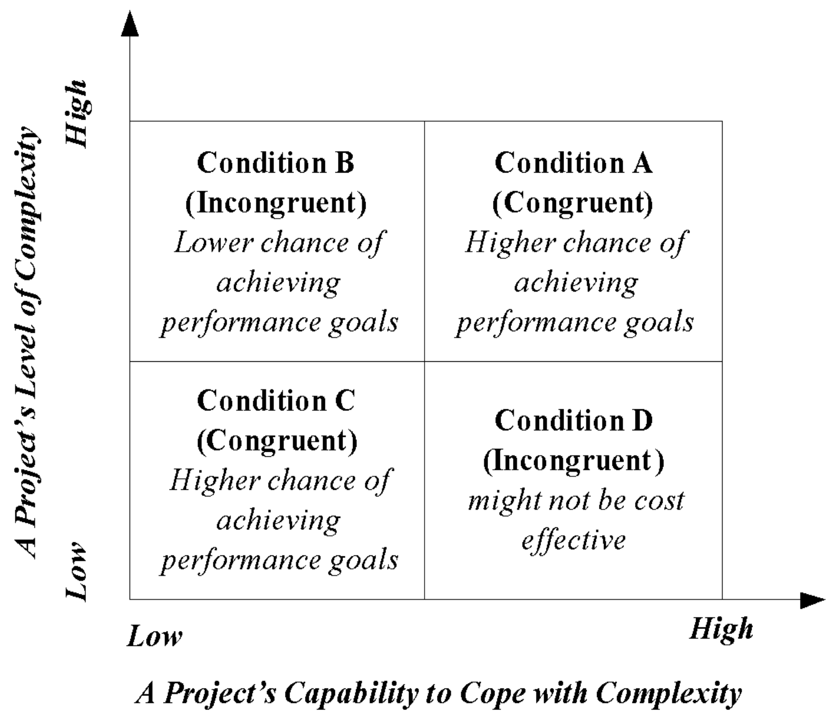


Figure 3-1 Relationships between Complexity and Capability to Cope with Complexity

Performance assessment based on contingency theory can effectively address the limitations in traditional approaches. First, it emphasizes the existence of different levels of complexity and their possible impacts on project performance. Second, it assesses project performance based on the interactions between complexity and a project system's capability to cope with complexity, which provides an integrated approach to studying project performance. Third, performance assessment based on contingency theory provides prescriptive insights because it can help organizational design move towards a better congruence. Existing literature has already identified contingency theory as a promising approach for better understanding, designing, and managing projects (Levitt et al., 1999;

Shenhar, 2001; Hanisch & Wald, 2014). In order to develop an integrated theory of performance assessment in complex construction projects using contingency theory, a thorough understanding of both project complexity and project capability to cope with complexity is needed. While many studies on project complexity can be found in existing literature, studies on projects' capability to cope with complexity are rather limited.

3.2.3 Emergent properties

In this study, a project's capability to cope with complexity is investigated using theoretical underpinnings from complex system science. Based on complex system theory, the behaviors of complex system are greatly affected by emergent properties that stem from interactions between the components of complex systems and the environment (Johnson, 2006). Emergent properties, as integrative system characteristics, cannot be attributed to any single component of a complex system (Sage & Cuppan, 2001). Emergent properties, as a new dimension in understanding the behaviors and performance of complex systems, have been investigated in various complex systems such as ecosystems, infrastructure systems, and financial systems (Francis & Bekera, 2014; Anand, Gai, Kapadia, Brennan, & Willison, 2013).

Modern construction projects are essentially complex systems composed of multiple interrelated processes, activities, players, resources, and information (Zhu & Mostafavi, 2014a). As complex entities, the behaviors and capabilities of project systems are not only affected by how well each of the individual components is, but also contingent on how well different components work together for the good of the project as a whole. Thus, the ability of a project to cope with complexity can be attributed to one or multiple emergent properties in project systems. This understanding is essential in developing project systems that have the required attributes to cope with complexity. Despite the significant impacts of emergent properties on project performance, our knowledge about the emergent properties of construction projects related to each project's capability to cope with complexity is rather limited. One objective of this study is to identify and investigate project emergent properties affecting the ability of project systems to cope with complexity.

3.3 Complexity and Emergent Property Congruence (CEPC) Framework

A Complexity and Emergent Property Congruence (CEPC) framework is being proposed here as a novel approach to understand and assess project performance at the interface of project complexity and emergent properties. Figure 3-2 shows different components of the proposed CEPC framework. The first component of the CEPC framework evaluates a project’s level of complexity from two aspects: detail complexity and dynamic complexity. The second component considers three emergent properties (i.e., absorptive capacity, adaptive capacity, and restorative capacity) affecting a project’s overall capability to cope with complexity. Based on the evaluations of emergent properties and complexity in a specific construction project, the level of congruence between the two components in the project systems can be used for a better understanding of project performance outcomes. In general, a project with a greater congruence will have a greater likelihood of attaining project performance goals. In this section, each dimension of project complexity and emergent properties in the proposed framework is explained in detail.

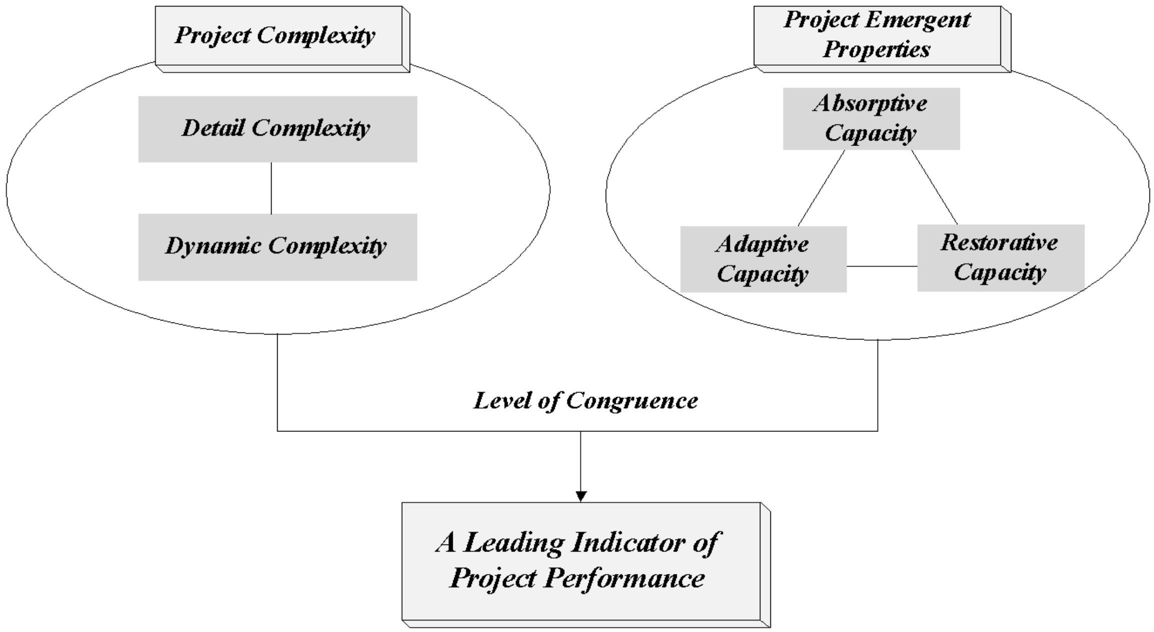


Figure 3-2 Complexity and Emergent Property Congruence (CEPC) Framework

3.3.1 Project complexity

Complexity is being used as an umbrella term associated with difficulty and interconnectedness in project systems (Geraldi & Adlbrecht, 2007). Baccarini (1996) identified two types of complexity in project systems: organizational and technological complexity. Williams (1999) further elaborated Baccarini's conceptualization of project complexity and attributed both organizational and technological complexity to structural complexity, and considered uncertainty as another dimension. Ever since, different researchers have developed various frameworks to better understand, categorize, and measure project complexity from different perspectives. For example, Geraldi & Adlbrecht (2007) classified complexity into three types: complexity of faith (the complexity involved in creating something unique, solving new problems, or dealing with high uncertainty), complexity of fact (the complexity in dealing with a huge amount of interdependent information), and complexity of interaction (the complexity related to interfaces of locations, such as politics, ambiguity, multiculturality). Bosch-Rekveldt et al., (2011) proposed the Technical, Organizational, and Environment (TOE) framework to assess the complexity of engineering projects. Using the TOE framework, the complexity of engineering projects can be assessed from technological complexity (related to goals, scope, tasks, experience, and risk), organizational complexity (related to size, resources, project team, trust, and risk), and environment complexity (related to stakeholders, location, market conditions, and risk). He, Luo, Hu, & Chan (2013) used a six-category framework of project complexity, composed of technological, organizational, goal, environmental, cultural, and information complexities, to measure the complexity of construction mega-projects.

In this study, complexity of construction project systems is evaluated based on two dimensions: detail complexity and dynamic complexity. Detail complexity and dynamic complexity are two concepts initially introduced by Senge (2006). According to Senge (2006), there are two types of complexity in any system: detail complexity (which arises from a large number of variables) and dynamic complexity (which arises from the relationships between the components where cause and effect may not be clear and may vary over time). Hertogh & Westerveld (2010) used these classifications for explanation of complexity in large infrastructure projects. Since the proposed CEPC framework investigates projects as complex systems, the proposed framework adopts the complexity classification provide by both Senge (2006) and Hertogh & Westerveld (2010).

(1) Detail complexity

Detail complexity is time-independent complexity that is determined by the structure of a system (Elmaraghy, Elmaraghy, Tomiyama, & Monostori, 2012). Hertogh & Westerveld (2010) described detail complexity as the existence of “many components with a high degree of interrelatedness”. Thus, detail complexity in construction projects is mainly related to the structural features of a project (e.g., project size, number of stakeholders, relationships between different components of the buildings or facilities, interfaces between different trades and stakeholders). Detail complexity depends on project scope, objectives, and characteristics, and does not change over time.

(2) Dynamic complexity

Dynamic complexity is time-dependent complexity and deals with the operational behaviors of a system (Elmaraghy et al., 2012). Hertogh & Westerveld (2010) attributed dynamic complexity to “the potential to evolve over time” and “limited understanding and predictability.” In construction projects, dynamic complexity is associated with the non-predictable and non-linear nature of projects. Dynamic complexity of a project is affected by both internal factors (e.g., human behaviors, material flow, and development in requirement and scope) and external factors (e.g., social, political and economic issues, and weather conditions). Dynamic complexity, as the term implies, changes over time and thus cannot be evaluated at the beginning of a project.

Assessing detail complexity and dynamic complexity in the proposed framework enables project managers and decision-makers to assess and deal with different types of complexity by using different strategies. According to Senge (2006), most of the conventional forecasting, planning, and analysis methods are equipped to deal with detail complexity instead of dynamic complexity. However, the real leverage in most management situations lies in understanding the dynamic complexity.

3.3.2 Project emergent properties

Emergent properties are distinguishing traits of complex systems. Emergent properties arise from interactions and interdependencies of constituents in complex systems and greatly affect system-level behaviors and performance (Johnson, 2006). In this study, investigation of emergent properties in construction projects was considered as a new approach in understanding a project's capability to cope with project complexity. There are various emergent properties of complex systems in the existing literature, such as resilience, vulnerability, agility, flexibility, and adaptive capacity (Francis & Bekera, 2014; Park, Seager, Rao, Convertino, & Linkov, 2013; Zhang, 2007; Phillips & Wright, 2009; Folke, Hahn, Olsson, & Norberg, 2005). Among a list of different emergent properties, three of them are closely related to a system's ability to cope with complexity: absorptive capacity, adaptive capacity and restorative capacity.

(1) Absorptive capacity

The first emergent property that affects the ability of project systems to cope with complexity is absorptive capacity. Absorptive capacity captures a project's level of preparedness for complexity. A project system with a high level of absorptive capacity can absorb the impact of both complexity and uncertainty, and minimize the consequences with little effort (Francis & Bekera, 2014). In other words, a project with a high level of absorptive capacity can operate successfully in complex contexts without changing its initial governance structure and execution processes.

(2) Adaptive capacity

Adaptive capacity refers to a project's ability to reconfigure itself in terms of organizational structure or execution processes in response to complex situations (Folke et al., 2005). A project's adaptive capacity is related to its speed and ease in making changes in order to maintain or enhance performance outcomes. A project with a high level of adaptive capacity can adjust itself quickly in order to prevent negative effects on project performance due to complexity, while a project with a low level of adaptive capacity may be slow and have difficulty in making changes in coping with complexity.

(3) Restorative capacity

Restorative capacity, also referred to as recoverability, is a project's ability to recover quickly from disruptions due to complexity (Francis & Bekera, 2014). When a project's absorptive capacity and adaptive capacity are not sufficient to cope with the undesirable effects of complexity, the project may experience organizational dysfunction and performance deviation. Restorative capacity enables a project to recover and return to the desirable performance level. A project with a high level of restorative capacity can recover quickly from the complexity-induced negative impacts.

Absorptive capacity, adaptive capacity, and restorative capacity are all emergent properties arising from interdependencies and interactions between various constituents in projects. For example, they are all closely related to effective communication and collaboration between different stakeholders and participants across different levels in project organizations. These three emergent properties are mutually exclusive and collectively exhaustive. In other words, each of the three emergent properties represents different attributes related to the ability of a project system to cope with complexity. Collectively, these three emergent properties can well depict and fully capture a project's capability to cope with complexity.

3.4 Methodology

In order to verify the proposed framework and further identify various factors affecting the complexity elements and emergent properties, a qualitative research approach was adopted in this study through semi-structured interviews conducted with senior project managers in the construction industry. Qualitative research approaches are extremely useful in exploratory studies aimed at identifying new concepts and frameworks. Information obtained from qualitative research provides insights into problems and helps to discover and develop new theories (Glaser & Strauss, 2009). Since there is a limited understanding on project complexity and emergent properties in the context of construction projects, interviews with senior project managers who have rich experience in construction industry can help verify the proposed framework and create theoretical constructs that explain the concepts in the framework. In the following section, the process related to collection and analysis of data is explained.

3.4.1 Crafting protocols

Development of the interview protocol is an important task in semi-structured interviews. The quality of the protocol directly affects the quality of the study (Rabionet, 2011). In this study, the interview protocol included an introduction component and an open-ended question component. An effective introduction is important in interviews in order to establish rapport, to create an adequate environment, and to elicit reflection and truthful comments from the interviewees (Rabionet, 2011). During the introduction phase, the interviewers introduced themselves and collected the basic information (e.g., year of working experience in construction industry, number of construction projects participated) of the interviewees. A statement of confidentiality and use of the results was provided to the interviewees. A brief introduction of research objective and background information was given to the interviewees in order to lead them to link the context with their experiences in the construction industry.

The question component included open-ended questions related to project complexity (i.e., detail complexity and dynamic complexity) as well as project emergent properties (i.e., absorptive, adaptive and restorative capacity). For each dimension of project complexity and emergent properties, several questions were asked. First, questions about the existence and impacts of each dimension of project complexity and emergent properties were asked in order to verify the proposed framework. If the interviewees confirm the existence of that specific dimension, follow-up questions related to the contributing factors to that dimension of project complexity or emergent properties were asked. For example, the questions related to project dynamic complexity included the following: *"Project complexity could evolve and increase during the implementation stage of construction projects due to different factors (e.g. unexpected human agent actions, or delayed material delivery). Have you ever experienced an increase of project complexity caused by such factors? If yes, can you give us some examples of construction projects in which project complexity increased overtime and what were the consequences?"* The objectives of questions such as this were to lead the interviewee to explain and elaborate his/her experience from the previous projects about dynamic complexity, and get information about factors contributing to dynamic complexity from examples provided by interviewees.

Similar questions were asked to verify and evaluate emergent properties in project systems. For example, the questions related to project adaptive capacity were as follows: *"Most of the time, project organizational structures or execution processes would change to some extent to adapt to the unexpected events happening during the implementation stage of a construction project. Have you had any experience with such situations? Do you find a difference between different projects in terms of their speed and ease in adapting to changes? Can you give us some examples of your previous projects that adapted to the changes successfully? What specific traits can you find in those projects?"* The objectives of these questions such as the one above were to verify that different emergent properties exist in project systems and to obtain knowledge on factors affecting different emergent properties.

3.4.2 Data collection

The data collection process started with identifying the target interviewees. Senior project managers who have at least 10 years of experience in the construction industry were identified as the target interviewees, since they were able to provide comparative insights regarding different projects in terms of various project complexity, emergent properties, and their impacts on project performance. A snowball sampling (referral sampling) method was used to identify the target interviewees. The snowball sampling method, which is widely used in qualitative sociological research, yields a study sample through referrals made by people who share or know of others who possess some characteristics that are of research interest (Biernacki & Waldorf, 1981). In using this method, nineteen senior project managers in the construction industry were interviewed during February to October 2014. This sample size was determined based on an observation of information redundancy and theoretical saturation from the conducted interviews (Sandelowski, 1995). Among the nineteen interviews, three were conducted on the telephone and the remainder through face-to-face meetings. Each interview lasted between forty-five minutes to one hour. Most of the interviewees were working in the South Florida area of the United States. However, since the interviews aimed at collecting data from the interviewees' previous experiences as construction project managers, the data they provided covered projects in different locations in the United States, as well as international projects.

During the course of this research, two researchers conducted the interviews together. The two interviewers had independent roles. One interviewer took the lead in asking questions, while the other interviewer took notes, recorded the conversations upon permission, and made observations.

3.4.3 Data analysis

Comparative analysis (Thorne, 2000) was adopted for data analysis in this study. NVivo software was used during data analysis. Figure 3-3 shows the process of data analysis. First, the interviews were transcribed verbatim and imported into the NVivo software. Second, five parent nodes were created in NVivo based on the concepts in the proposed framework: detail complexity, dynamic complexity, absorptive capacity, adaptive capacity, and restorative capacity. Then the interview data was reviewed in NVivo. During the review, multiple child nodes related to each parent node were identified and created from the data. These child nodes were recognized as the contributing factors to each parent node. Each phrase or sentence in the interview data that signified the child nodes was coded as a reference of the corresponding child nodes. The total number of references of each child node was obtained when all the interview data was reviewed. Accordingly, the number of references for a parent node was obtained as the sum of all the references of its child nodes. A higher number of reference coded to each node indicated similar patterns and frequent occurrence of opinions across different interviews. Thus the data analysis results could be used to verify the existence and importance of different dimensions of project complexity and emergent properties in the proposed framework, as well as to identify the most significant contributing factors to those dimensions. The findings from the data analysis are illustrated in the following section.

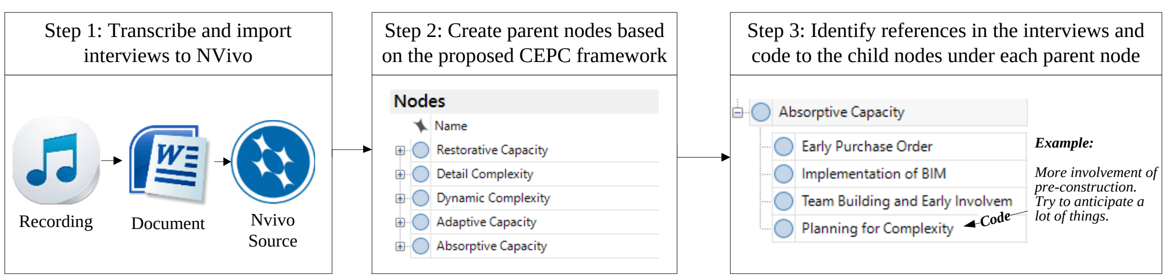


Figure 3-3 Data Analysis Process

3.5 Results

Almost all interviewees reported that they observed different levels of project complexity (i.e., detail complexity and dynamic complexity) as well as the emergent properties (i.e., absorptive capacity, adaptive capacity and restorative capacity) to some extent across different projects. There was also a consensus of opinions among different interviewees that overall a higher level of project complexity brings more difficulties for projects being finished on time and on budget, and better absorptive, adaptive and restorative capacities could help to minimize the negative impacts of complexity. From the interview data, factors contributing to different dimensions of project complexity and emergent properties were identified. In this section, the analysis results are presented by each dimension of project complexity and emergent properties.

3.5.1 Project complexity

From the transcribed interview data, child nodes denoting the contributing factors to detail complexity and dynamic complexity were identified. Based on the experiences of interviewees, these factors lead to different levels of project complexity. Figure 3-4 shows the child nodes and their number of references identified from the interview data.

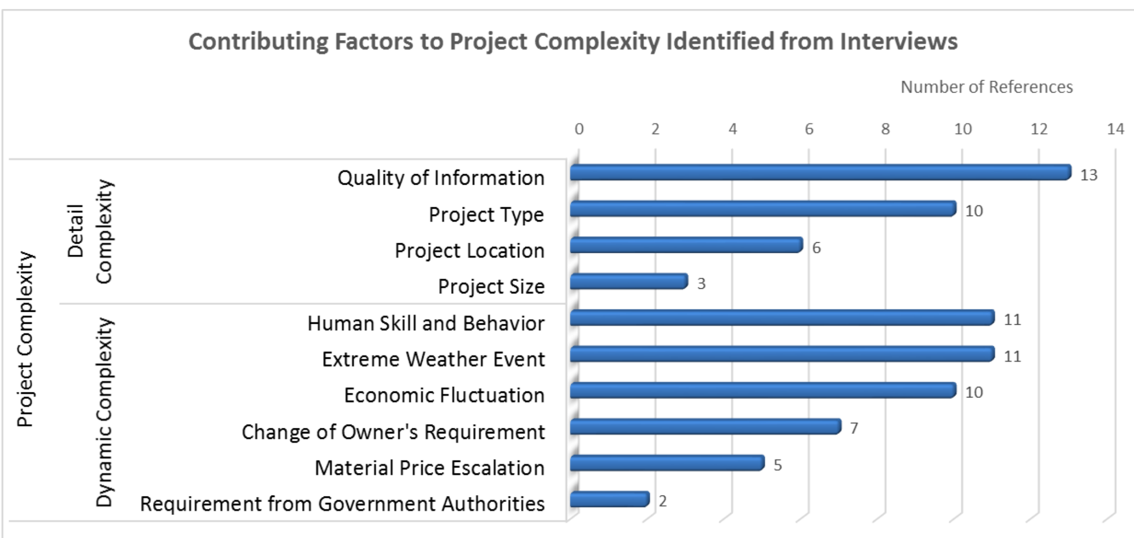


Figure 3-4 Contributing Factors to Project Complexity, as Identified from Interviews

(1) Detail complexity

Detail complexity is inherent project complexity that exists at the beginning of a project. From the interviews, four child nodes of project detail complexity were identified across the responses of different interviewees: quality of information, project type, project location, and project size. Examples were provided by interviewees regarding how these factors caused different levels of complexity in different construction projects and how they led to different project performance outcomes. For example, the factor related to detail complexity most mentioned during the interviews was the quality of information (e.g., existing conditions, soil test results, design and drawings). Interviewees pointed out that many of the unexpected conditions at construction jobsites were due to inaccurate or conflicting information. For instance, as-built drawings, as one example of important project information, do not always reflect the real situation. According to one of the interviewees, "*When you get to the project location, some infrastructures that were on the drawings might not exist, or are maybe in a different location*." Under these circumstances, more time and money will be spent on correcting the information in order to continue with the work. Sometimes an unknown existing condition (e.g., unexpected underground pipes) could cause a devastating effect on the project. Project type is another significant factor affecting project detail complexity. Renovation projects were identified as more complex than new projects by the interviewees. According to many of the interviewees, "*doing projects in existing buildings*" brings more difficulties, because such projects require more information on existing conditions and have strict space constraints. Other aspects pertaining to detail complexity of construction projects include project location and size. Project location could increase project complexity due to logistic issues. For example, projects in urban areas are more complex as there is usually "*limited room to lay down equipment and place material.*" Project size was identified by several interviewees as important, since "the *larger the project, the greater the number of people involved.*" However, several interviewees acknowledged that project size alone cannot determine the level of complexity of a project. As one of the interviewee said, "*A small project can be very complex, while a big project can be very simple*." Project size, as a contributing factor to project complexity, needs to be jointly considered and evaluated along with other factors.

(2) Dynamic complexity

Dynamic complexity emerges and evolves during project execution. Six child nodes of project dynamic complexity were identified in the interview data: human skill and behavior, extreme weather event, economic fluctuation, change of owner's requirements, material price escalation, and requirement from government authorities. During the interviews, respondents used their experiences to explain the influence of these factors on project complexity and performance outcomes. Human skill and behavior was identified as the most significant factor affecting project dynamic complexity. According to the information provided by the interviewees, human errors and omissions in construction projects, including "*ordering wrong material*," "*installing product incorrectly,*" "*unsafe acts,*" and "*violating working regulations,*" could greatly affect project performance. One interviewee specifically emphasized the impact of risk attitude of workers on project complexity: "*There are more risk takers in some trades. For example, people in the steel industry are referred to as 'cowboys' as they are used to working at great heights. So if there are more steel workers in one project, it is more likely for them to take shortcuts in work and create problems.*" Extreme weather event, such as hurricane, flood, and snowstorm, was identified as another significant contributing factor to project dynamic complexity due to the unpredictability and devastating impact. During the interviews, the respondents provided examples of delays and damages to their projects due to extreme weather events. For example, one interviewee mentioned that "*Whenever a hurricane comes, you need to shut down at least five to ten days.*" Another interviewee mentioned that a severe snowstorm in 2014 delayed the delivery of key materials and their project was suspended because of it. Economic fluctuation is another example of contributing factors to project dynamic complexity. It affects construction projects mainly through the availability of workers. For example, one interviewee gave an example related to the impact of economic fluctuation on construction projects in the South Florida area of the United States: "*For the past couple of years, much of the construction labor force left for other states or industries because of the slowdown in the construction industry due to the economic recession. Now that the economy is turning around and the construction industry starts to grow in South Florida, the availability of the labor force is limited.*" Other factors identified in the interview data which could increase project dynamic complexity include change of owner's requirement, material price escalation, and additional requirement from government authorities such as state and local agencies. Due to their uncertain natures, the above-mentioned factors contributing to project dynamic complexity are difficult to capture and deal with in construction projects.

3.5.2 Project emergent properties

From the transcribed interview data, child nodes denoting the contributing factors to absorptive capacity, adaptive capacity, and restorative capacity were identified respectively. Figure 3-5 shows the child nodes and their number of references identified from the interview data pertaining to project emergent properties.

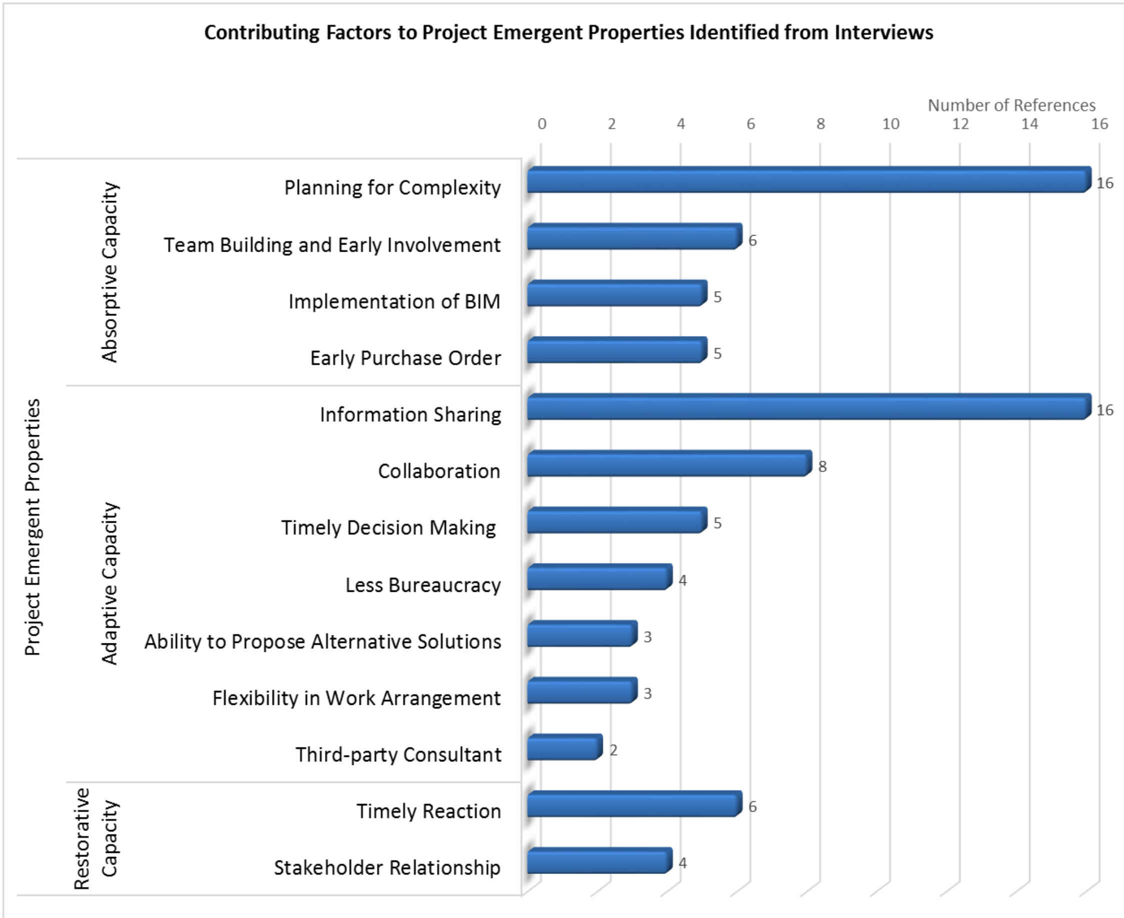


Figure 3-5 Contributing Factors to Project Emergent Properties, as Identified from Interviews

(1) Absorptive capacity

Absorptive capacity represents a project's ability to absorb the impacts of complexity with little effort. From the interviews, four child nodes of project absorptive capacity were identified as follows: planning for complexity, team building and early involvement, implementation of Building Information Modeling (BIM), and early purchase order. Interviewees confirmed that different practices pertaining to these four factors in projects could lead to different levels of absorptive capacity and different performance outcomes. The most significant factor is planning for complexity. Many interviewees mentioned that planning for complexity during the pre-construction phase was critical for enhancing the absorptive capacity of a project. According to the interviewees, projects with high levels of absorptive capacity are the ones that adopt strategies to prevent possible problems at early stages of a project. Examples of those planning strategies include "*avoiding scheduling certain activities such as pouring concrete during the hurricane season*" and "*eliminating possible conflicts between different trades by coordination of Mechanical, Electrical, and Plumbing (MEP) Systems from the design phase.*" In order to better plan for complexity, another important factor of project absorptive capacity, which is team building and early involvement, is needed. Early involvement of different stakeholders (e.g., owner, architecture, engineer, general contractor, subcontractors, and material suppliers) helps projects to move forward in complex environments. As indicated by one interviewee, "*The key is to ask participants to sit together, get familiar, understand the conditions, and address possible problems ahead of time.*" Another significant contributing factor to absorptive capacity was identified as implementation of BIM. Interviewees observed that projects that implemented BIM had higher absorptive capacity and better performance. Implementation of BIM in projects can improve the information exchange and coordination process between different stakeholders and trades, and thus possible conflicts in design and construction can be diagnosed and addressed before they cause harm to the projects. Finally, early purchase order was also identified as important to project absorptive capacity. According to interviewees, "*placing purchase orders for material and equipment early and locking in the price with suppliers*" is an effective strategy to deal with complexity factors related to price escalation or later delivery of materials and equipment.

(2) Adaptive capacity

Adaptive capacity represents a project's ability to quickly adapt to new situations and conditions. During the interviews, the importance of adaptive capacity in construction projects to project performance was highlighted by the interviewees. As one of the interviewees said, "*Our industry is built on estimation. But estimation is not guaranteed. Weather, labor, and resource are all factors that cannot be fully controlled. The ability to deal with circumstances which are not in the plan is important. If we cannot get material from somebody, we go to somebody else. If a subcontractor doesn't perform well, we may need to find a substitute. If we find contaminated soil in foundation work, we bring it to the attention of the owner and architect and make adjustments together. We are constantly adapting to the things we cannot control.*" From the interviews, seven child nodes of project adaptive capacity were identified, including information sharing, collaboration, timely decision making, less bureaucracy, ability in proposing alternative solutions, flexibility in work arrangement, and third-party consultant. Information sharing and collaboration are two closely related factors contributing to project adaptive capacity. As many of the interviewees highlighted, the key to adapting to new situations is to "*make everyone be aware of the situation as soon as possible.*" The sooner that different stakeholders have the information, the sooner they can coordinate with each other and come up with adaptation plans. Due to the high level of interdependencies in construction projects, any single adaptation action might affect other aspects and stakeholders. Thus a collaborative effort is extremely important in this process. Similarly, timely decision making and less bureaucracy are two closely related contributing factors to project adaptive capacity. The ability to make a timely decision is crucial in construction projects, especially when there is an emergency at a jobsite. Bureaucracy in projects could hinder timely decision making. For instance, one interviewee said that, "*Bureaucracy in some of the projects is a big problem. I once had to deliver different documents to different offices and get them reviewed and approved in order to make a small change in design to cope with emerging issues at the jobsite. By the time I finally got the approval, one week had already past.*" Other contributing factors to project adaptive capacity identified include the ability to propose creative alternative solutions to deal with complexity, flexibility in work arrangement such as activity sequences based on resource and space availability, and having a third-party consultant to provide independent professional advice and suggestions.

(3) Restorative capacity

Restorative capacity is the ability of a project to recover from disruptions due to complexity. Interviewees emphasized that not every construction project can quickly recover from disruptions. Contributing factors to project restorative capacity identified in the interview data were coded as two child nodes: timely reaction and stakeholder relationship. Timely reaction is important for projects to recover from disruptions. Typical recovery actions mentioned by interviewees include working overtime, increasing manpower, or bringing in additional help such as another sub-contractor. One interviewee highlighted the importance of timely reaction by using his experience during hurricane Katrina: "*After the hurricane flooded part of the jobsite, I just called workers immediately and asked them to come to work during night and fix the damaged exterior wall to stop more water from coming in, without waiting for change orders. With this quick reaction, the hurricane just* *delayed the schedule by a few days, which can be considered as a minimum impact to the project performance*.” In some other cases mentioned by the interviewees, if such quick reaction is not taken, disruptions can cause severe damages to the project. In order to achieve timely reaction, good relationships between stakeholders are essential. Restorative capacity in a projects arises from the cooperation and collaboration of different stakeholders. According to interviewees, when good relationships are maintained, those directly involved are more “*responsible*” and “*willing to help out*” in hard times.

3.6 Discussions and Concluding Remarks

This study presents a novel framework for integrated performance assessment in project systems. The proposed framework integrates theoretical underpinnings from complex systems and organizational sciences in order to advance the understanding of phenomena affecting the performance of complex construction projects. Using the proposed CEPC framework, the performance outcome of a construction project can be better understood and evaluated based on the congruency between project complexity and emergent properties. The proposed framework was verified through the use of qualitative data obtained from nineteen interviews with senior project managers in the construction industry. The analysis of the information obtained from the interviews verified the existence and significance of two dimensions of project complexity (i.e., detail complexity and dynamic complexity) and three dimensions of project emergent properties (i.e., absorptive capacity, adaptive capacity, and restorative capacity). In addition, the results identified significant contributing factors to different elements of complexity (e.g., quality of information, project location, and human skills and behaviors) and emergent properties (e.g., team building and early involvement, timely decision making, and stakeholder relationship).

The proposed CEPC framework has various novel contributions to the existing theory of performance assessment in project systems. First, this study integrated the theoretical underpinnings from complex systems (i.e., emergent properties) and organizational science (i.e., contingency theory) in order to create a novel theoretical lens into performance assessment in projects. Hence, the proposed framework provides the foundations for further interdisciplinary and integrated theories in the domain of project management. Second, the evaluation of projects as complex systems and recognition of the significance of emergent properties provides an innovative theoretical basis for better understanding of the various elements that affect project performance outcomes. In particular, this study is the first to identify emergent properties affecting the ability of project systems to cope with complexity. Despite the use of system thinking in existing project management theories, the understanding of emergent properties in projects has been limited. A better understanding of emergent properties in project systems will enhance the understanding of the situations leading to performance inefficiencies in projects. Based on the proposed CEPC framework, future studies can develop quantitative metrics, integrated decision support tools, and reliable methods for monitoring and evaluating project complexity and emergent properties in construction projects. For example, a leading indicator of project performance based on the level of congruence between project complexity and emergent properties can be created and tested.

From a practical perspective, the project managers and decision makers can use the contributing factors identified in this study as a guide for enhancing absorptive capacity, adaptive capacity, and restorative capacity in their projects. One of the major reasons behind performance inefficiency is that the level of project emergent properties is not sufficient to cope with project complexity. Based on the findings of this study, project managers and decision makers can adopt different planning strategies (e.g., implementation of BIM, early involvement of contractors, or improving stakeholder relationships by establishing partnership) in order to increase the possibility of project success by enhancing different project emergent properties.

4. META-NETWORK FRAMEWORK FOR INTEGRATED PERFORMANCE ASSESSMENT UNDER UNCERTAINTY

The objective of this chapter is to create and test an integrated framework for assessment of vulnerability to uncertainty in complex projects. In the proposed framework, construction projects are conceptualized as meta-networks composed of different nodes (i.e., human agents, information, resources, and tasks) and links. The effects of uncertain events are translated into perturbations in the nodes and links of project meta-networks. These uncertainty-induced perturbations are reflected as transformations in a project's topological structure, and thus negatively affect the efficiency of the project meta-network. The extent of the variation in the efficiency of a project's meta-network is used to determine the extent of vulnerability to uncertainty. The application of the proposed framework is shown in an illustrative case study related to a tunneling project. In the case study, various scenarios related to different uncertain events were simulated through the use of dynamic network analysis and Monte-Carlo simulation. The illustrative case study demonstrated the application of the proposed framework for predictive assessment and proactive mitigation of vulnerability to uncertainty based on evaluation of dynamic interactions between various entities and networks in construction projects. The proposed framework integrates elements from complex systems, dynamic network analysis, and Monte Carlo simulation approaches and provides a novel computational framework for ex-ante evaluation of vulnerability to uncertainty in civil engineering projects. This chapter has been published as Zhu & Mostafavi (2016).

4.1 Introduction

Performance inefficiency is a major challenge in the construction industry. For example, based on a study of 258 transportation infrastructure projects across 20 nations, Flyvbjerg et al., (2003) showed that nine out of ten transportation projects experienced cost escalation. In another study conducted by the Construction Industry Institute (CII), only 5.4% of the 975 construction projects studied met their planned performance objectives in terms of cost and schedule, while nearly 70% of these projects had actual costs or schedule exceeding +/- 10% deviation from their authorized values (Construction Industry Institute, 2012).

One important reason for the unpredictability of project performance is the high level of uncertainty in modern construction projects. As shown in Figure 4-1, the impact of uncertainty on the performance of construction projects is influenced by two phenomena: (1) the project's exposure to uncertainty, and (2) the project's sensitivity to perturbations due to uncertainty. Exposure to uncertainty is the extent to which a project is exposed to an uncertain environment. The greater the exposure to uncertainty, the greater the likelihood of uncertain events. A project's sensitivity is determined based on the degree to which the project is affected by uncertainty-induced perturbations. Different projects have varying levels of sensitivity to uncertainty-induced perturbations, depending on their traits and planning strategies. The combination of a project's exposure to uncertainty and its sensitivity to uncertainty-induced perturbations determines the vulnerability of the project to uncertainty. Similar to other complex systems, construction projects have a greater likelihood for successful performance if they are less vulnerable to uncertainty. Thus, a better understanding of project vulnerability is critical for creation of an integrated theory of performance assessment.

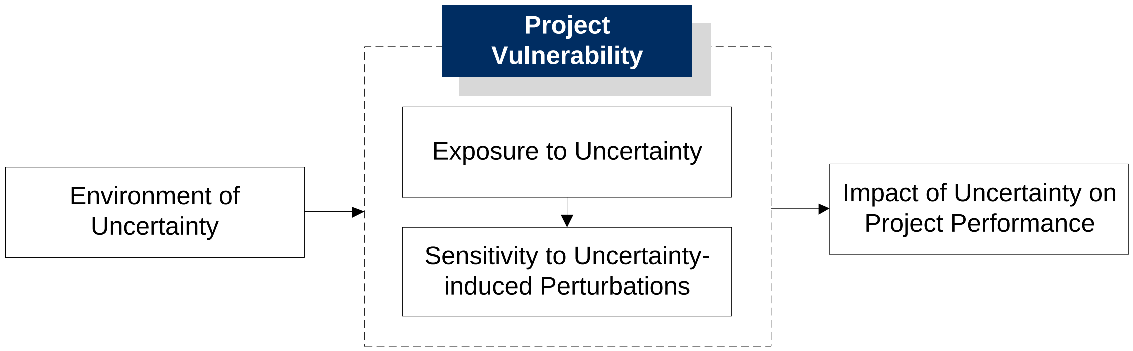


Figure 4-1 The Mechanism of Impact of Uncertainty on Project Performance

The conventional paradigms in assessment of performance under uncertainty in construction projects have various limitations. First, the existing body of knowledge fails to inform about project vulnerability to uncertainty. The existing studies mainly focus on identification and evaluation of risk factors, their likelihoods, and their impacts. Researchers have identified the key risk factors (e.g., shortage in materials and labor supply, changes in design, unavailability of funds) in construction projects by using questionnaire surveys, interviews with subject-matter experts, and case studies (Choudhry, Aslam, Hinze, & Arain, 2014; El-Sayegh, 2008; Zou et al., 2007). However, the understanding of project vulnerability to uncertainty remains very limited. In fact, the existing knowledge does not inform about factors influencing vulnerability to uncertainty, quantitative measures of project vulnerability, or ways to reduce project vulnerability. Second, the existing studies do not capture the dynamic interaction and interdependencies between various entities in the assessment of performance and uncertainty in construction projects. Construction projects are complex systems composed of interconnected entities (i.e., human agents, information, resources, and tasks) and operate in uncertain environments (Zhu & Mostafavi, 2014c). In fact, project vulnerability is an emergent property that arises from the interactions and interdependencies between different entities. The lack of an integrated framework for the analysis of interactions and interdependencies between various entities in construction projects has hindered the creation of an integrated theory of performance assessment. Third, the existing approaches in assessment of performance and uncertainty in construction are reactive in nature. Uncertain risk factors are identified as projects progress and mitigation plans are developed accordingly. However, the impacts of uncertainty can be more effectively mitigated during project planning. A more proactive approach requires evaluation of project vulnerability to uncertainty during planning in order to effectively determine strategies to mitigate the impacts of uncertainty on project performance.

To address the limitations in the existing body of knowledge related to the assessment of performance and uncertainty in projects, recent studies have emphasized the importance of considering project vulnerability. Zhang (2007) redefined the process for project risk assessment through the evaluation of project vulnerability. According to Zhang (2007), the impact of uncertainty on project performance depends on both risk events and project systems. Consideration of project vulnerability is an emerging field directed at addressing the exiting knowledge gaps in assessment of performance and uncertainty in projects. Appropriate conceptualization and analysis of project vulnerability is a critical missing component in enabling the creation of an integrated theory of project performance assessment under uncertainty. To address these gaps in the body of knowledge, the study presented in this paper adopts the theoretical underpinnings from network theory and complex system sciences in order to create an integrated framework for conceptualization, quantitative analysis, and measurement of project vulnerability. The proposed framework enables predictive assessment and proactive mitigation of project vulnerability in order to reduce the impacts of uncertainty on the performance of construction projects.

4.2 Framework for Vulnerability Assessment

This study adopts the theoretical underpinnings from complex systems science and network theory in order to create a framework for conceptualization and modeling of project vulnerability. Based on complex system science, the macro-level emergent behaviors of complex systems can be captured and modeled through attributes and interdependencies of base-level constituents. Complex system science has been used in understanding the complex behaviors of civil engineering and infrastructure projects (Locatelli, Mancini, & Romano, 2014; Mostafavi, Abraham, & DeLaurentis, 2014). In the proposed framework, projects are conceptualized as interconnected and heterogeneous meta-networks composed of four types of base-level entities: human agents, information, resources, and tasks. This conceptualization is based on abstraction and evaluation of projects as complex systems in which human agents utilize information and resources to implement different tasks at the base-level (Zhu & Mostafavi, 2014a). Using this conceptualization, emergent properties (such as vulnerability) in projects can be captured from dynamic interdependencies between different entities (i.e., human agents, information, resources, and tasks) (Zhu & Mostafavi, 2015a). Dynamic Network Analysis (DNA) is another important aspect of theoretical background based on which the proposed framework is built. DNA is an emergent field in network theory (Carley, 2003). Different from traditional social network analysis (SNA), DNA is capable of investigation of large dynamic networks composed of multiple types of nodes and links with varying levels of uncertainty (Carley, 2003). In DNA, the links in a meta-network are probabilistic and can change over time based on the impacts of uncertainty. Quantitative measurements at the meta-network level in DNA facilitate studying complex systems using computational and mathematical approaches. Recent studies have successfully implemented DNA in assessment and optimization of performance in civil engineering projects (Li, Lu, Li, & Ma, 2015; Zhu & Mostafavi, 2015a). The proposed framework in this study is developed using concepts and quantitative measures of meta-networks in DNA. The probabilistic and dynamic nature of DNA enables the investigation of project vulnerability to uncertainty using Monte Carlo simulation.

The proposed meta-network framework for vulnerability analysis includes four components. Fig. 2 shows the four components of the proposed framework: (1) abstraction of project meta-networks, (2) translation of uncertainty; (3) quantification of project vulnerability, and (4) evaluation of planning strategies.

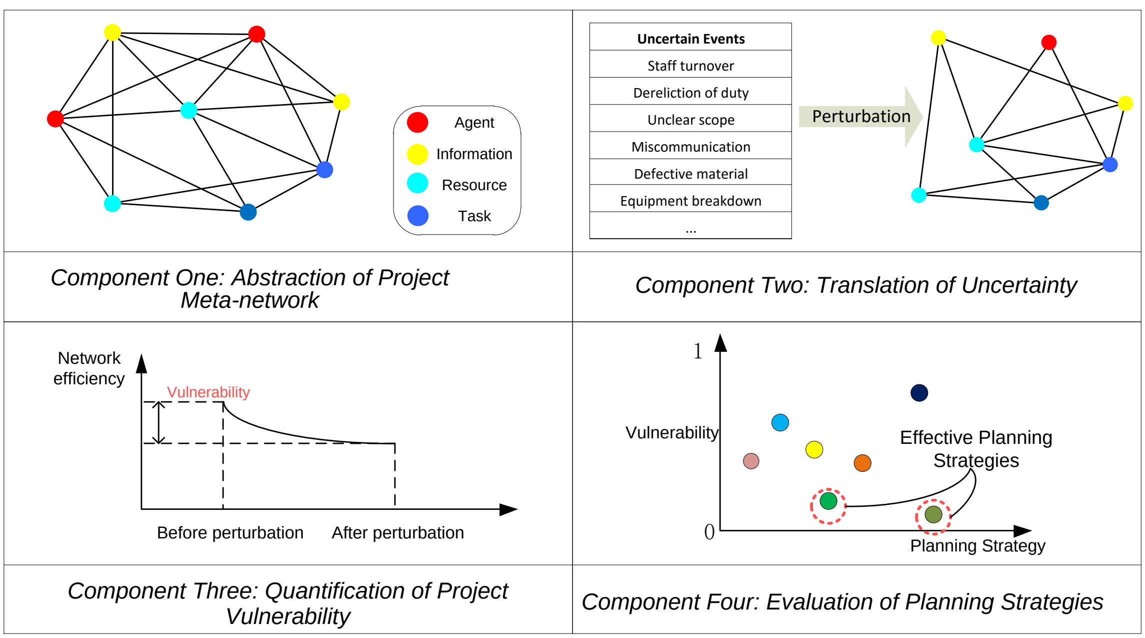


Figure 4-2 A Meta-network Framework for Vulnerability Assessment in Construction Projects

4.2.1 Abstraction of project meta-networks

Construction projects are complex systems (meta-networks) composed of interconnected human agents, information, resources, and tasks (Zhu & Mostafavi, 2014c). In a project meta-network, there are four types of node entities (i.e., agents, information, resources, and tasks) and ten primitive types of links (Table 4-1). Each set of links and their corresponding nodes can form an individual network. For example, the agent nodes and links connecting agent nodes form the Social Network in a project, representing the interactions between different human agents (i.e., who works with and/or reports to who). The agent and task nodes and links connecting agent nodes with task nodes form the Assignment Network in a project, showing the task assignments (i.e., who is assigned to what task). In total, there are ten networks in a project, as shown in Table 4-1. These individual networks are interconnected with each other via the shared nodes and thus form a network-of-networks (i.e., meta-network). In a project meta-network, changes in one network cascade into changes in other networks, therefore influencing the overall performance of the project (Carley, 2003).

Table 4-1 Individual Networks in Project Meta-networks

	Agent	Information	Resource	Task
Agent	Social Network (AA): *Who works with and/or reports to who*	Information Access Network (AI): *Who knows what*	Resource Access Network (AR): *Who can use what resource*	Assignment Network (AT): *Who is assigned to what task*
Information		Information Network (II): *What information is dependent on what information*	Necessary Expertise Network (IR): *What information is needed to use what resource*	Information Requirement Network (IT): *What information is needed to do what task*
Resource			Resource Interdependence Network (RR): *What resource is needed for using what resource*	Resource Requirement Network (RT): *What resource is needed to do what task*
Task				Precedence Network (TT): *What task is precedent to or dependent on what task*

Abstraction of node entities and their links is the first component of the proposed framework. To abstract the node entities and links in a project meta-network (Figure 4-3), the first step is to identify the task nodes in a project. In a project meta-network, tasks include not only production work with measurable outcomes (e.g., conduct structural design, excavation, rebar installation), but also information processing and decision-making tasks (e.g., request for information, report unforeseen condition, decide on work sequence). A task needs to be implemented by one or more human agents. Thus, after identification of the task nodes, the agent nodes (i.e., human agents assigned for implementing the tasks) can be abstracted. An agent node can be an individual, a crew, or a team, depending on the nature of a task. Agents need certain information and resources to complete the tasks assigned to them. For instance, for a crew to install rebar at a jobsite, the crew needs relevant information (e.g., shop drawing and specifications) and resources (e.g., rebar and stirrups). Based on the requirements of different tasks, the information and resource nodes can be identified and abstracted. After all the nodes in a project are abstracted, the next step is to abstract the links between different nodes in a project meta-network. These links can be identified by answering different questions, such as those listed in Table 4-1. For example, by answering the question “What information is needed to do what task?” the links between information nodes and task nodes can be identified. Abstraction of a project meta-network is completed when all the node entities and links between the nodes are identified.

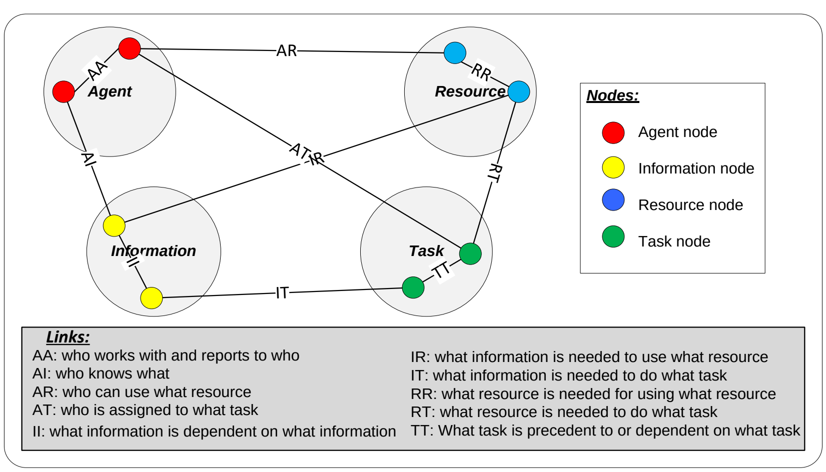


Figure 4-3 Abstraction of Construction Project Meta-networks

4.2.2 Translation of uncertainty

In network theory and complex systems science, uncertainty affects a system by causing perturbations (disturbances) in the system (Gallopín, 2006). Similarly, in the proposed framework, the effects of uncertainty are translated into uncertainty-induced perturbations in a project's meta-network. Perturbation effects are incorporated in the framework through removal of corresponding nodes and/or links in a project meta-network. Depending upon the nodes and/or links affected by uncertain events, there are three types of perturbation effects: (1) agent-related, (2) information-related, and (3) resource-related. An agent-related perturbation removes an agent node and all of its corresponding links from a project meta-network. An information-related perturbation removes all the links between an information node and agent nodes. Similarly, a resource-related perturbation removes all the links between a resource node and agent nodes.

In the proposed framework, uncertain events are abstracted based on two attributes: (1) likelihood of occurrence and (2) perturbation effects. The likelihoods of the uncertain events can be estimated either by historical data (e.g., occurrence of severe weather in certain areas during hurricane season, or defect rate of materials from certain suppliers) or through the use of probability encoding techniques in order to extract and quantify individuals' judgments about uncertain quantities (Spetzler & Stael von Holstein, 1975). The perturbation effects of uncertain events are determined based on the node entities and links impacted due to uncertain events. One uncertain event can result in single or multiple perturbation effects of one or different types. For example, breakdown of a lifter on a jobsite may lead to a resource-related perturbation (i.e., removal of the links between the lifter node and agent nodes), while failure of a power system, which provides power to multiple pieces of equipment, may cause multiple resource-related perturbations (i.e., removal of links between multiple equipment nodes and agent nodes). In another example, severe weather, could induce multiple effects including agent-related, information-related and resource-related perturbations. Table 4-2 provides examples of uncertain events and their corresponding perturbation effects in construction projects.

Hence, in the proposed framework, each uncertain event (e) is defined as:

$$e = (L, PE) \tag{4.1}$$

where L represents its likelihood of occurrence, and PE represents perturbation effects. Accordingly, the uncertain environment (E) surrounding a construction project can be defined as a set of uncertain events:

$$E = \{e_1, e_2, \dots, e_n\} \tag{4.2}$$

where n is the total number of possible uncertain events in a construction project. In the second component of the proposed framework, the uncertain environment of a project is determined and the likelihood and perturbation effects of each uncertain event are defined.

Table 4-2 Examples of Uncertain Events and Perturbation Effects in Construction Projects

	Perturbation Effect Type	Examples of uncertain event
Single-effect Event	Single agent-related perturbation	Staff turnover, safety accident or injury, dereliction of duty
	Single information-related perturbation	Late design deliverables, unclear scope/design, limited access to required information, miscommunication
	Single resource-related perturbation	Counterfeit/defective materials, equipment breakdown, late delivery of materials
Multi-effect Event	Multiple perturbation effects	Power system failure, severe weather, economic fluctuation

4.2.3 Quantification of project vulnerability

Based on translating the effects of uncertain events into uncertainty-induced perturbations in project meta-networks, the concept of "attack vulnerability" from network science can be used in order to quantity the project vulnerability. In network science, "attack vulnerability" is used to measure the response of networks subjected to attacks on nodes and links (i.e., selected removal of nodes and/or links) (Criado, Flores, Hernández-Bermejo, Pello, & Romance, 2005; Holme, Kim, Yoon, & Han, 2002). Attack vulnerability denotes the extent of decrease in network efficiency (how good a network functions) caused by the selected removal of nodes and/or links (Latora & Marchiori, 2004). Similar to other types of networks, the vulnerability of a project meta-network can be measured based on the extent of the changes in network efficiency prior and after perturbations. The greater the change in a project's meta-network efficiency due to perturbations, the greater the vulnerability of the project. In the proposed framework, project vulnerability (v) is assessed using Equation 4.3:

$$v = f(N) - f(N') \tag{4.3}$$

where f denotes the efficiency function of project meta-networks; N represents the state of a project meta-network before perturbations; and N' represents its state after perturbations.

There are different approaches to assess the efficiency of a network depending upon the network type and purpose. In the proposed framework, the efficiency of a project meta-network is measured based on the percentage of tasks that can be completed by the agents assigned to them (i.e., based on whether the agents have the requisite information and resource to do the tasks) (Carley & Reminga, 2004). Task completion percentage is assessed from information-based and resource-based perspectives respectively. From the information-based perspective, first, the information gap matrix (N_I) is defined:

$$N_I = [(AT' \times AI) - IT'] \tag{4.4}$$

where AT is the binary matrix of the assignment network; AI is the binary matrix of information access matrix; and IT is the binary matrix of information requirement network. N_I finds the gaps between the required information for tasks and information obtained by human agents who are assigned for those tasks. In matrix N_I, if an element $N_I(i, j)$ is negative, it means that information j is not available for conducting task i. Based on the information gap matrix (N_I), the tasks that cannot be completed due to lack of information are captured in a set S_I:

$$S_I = \{i | 1 \leq i \leq |T|, \exists j: N_I(i, j) < 0\} \tag{4.5}$$

where T is a set of all the tasks in a project meta-network, and $N_I(i, j)$ is an element of matrix N_I at the i^{th} row and j^{th} column. Equation 4.5 means that for row i in information gap matrix N_I, if at least one element in that row is negative (i.e., at least one piece of required information is not available), task i is attributed to set S_I as a task that cannot be completed due to lack of information. Using the result of Equation 4.5, information-based task completion percentage (TC_I) can be calculated in Equation 4.6 by comparing the number of tasks that can be successfully completed (i.e., $|T| - |S_I|$) with the total number of tasks (i.e., $|T|$):

$$TC_I = \frac{|T| - |S_I|}{|T|} \tag{4.6}$$

The resource-based task completion percentage (TC_R) can be calculated using the same approach as information-based task completion percentage (TC_I). Equations 4.7-4.9 show the procedure for calculating resource-based task completion percentage by replacing the information-related matrices in Equations 4.4-4.6 above with resource-related matrices:

$$N_R = [(AT' \times AR) - RT'] \tag{4.7}$$

$$S_R = \{i | 1 \leq i \leq |T|, \exists j: N_R(i,j) < 0\} \tag{4.8}$$

$$TC_R = \frac{|T| - |S_R|}{|T|} \tag{4.9}$$

where AR is the binary matrix of resource access matrix; RT is the binary matrix of resource requirement network; N_R is the resource gap matrix; and S_R is the set of tasks that cannot be completed due to lack of resource.

The overall efficiency of a project meta-network (f) is then defined as the average of information-based and resource-based task completion percentages using results from Equations 4.6 and 4.9:

$$f = \frac{TC_I + TC_R}{2} \tag{4.10}$$

By calculating the levels of project meta-network efficiency prior and after perturbations and substituting the results into Equation 4.3, the quantitative value of project vulnerability can be obtained. The value of project vulnerability ranges from 0 to 1. A greater value of vulnerability indicates that a project is more vulnerable, and thus, has a higher chance to suffer from low performance efficiency under uncertainty.

4.2.4 Evaluation of planning strategies

The last component of the proposed framework is evaluation of planning strategies in terms of their influence on project vulnerability. The purpose of this component is to identify and prioritize the most effective strategies in order to reduce project vulnerability during the planning phase. There are two type of planning strategies that could affect project vulnerability, based on different mechanisms: (1) by influencing a project's exposure to uncertainty (i.e., affecting the likelihood of uncertain events); and (2) by influencing a project's sensitivity to uncertainty-induced perturbations (i.e., changing the topological structure of a project meta-network by adding or removing nodes and/or links). Table 4-3 provides examples of planning strategies of both types.

Table 4-3 Examples of Planning Strategies in Construction Projects

Influencing Mechanism	Planning Strategies		Effect in Project Meta-networks
Exposure to Uncertainty	Supplier Selection	Prequalification	Reduce exposure to material-related uncertainty
		Regular selection process	Do not affect exposure
	Information Processing and Communication	ICTs	Reduce exposure to information-related uncertainty
		Traditional Tools	Do not affect exposure
Sensitivity to Uncertainty-induced Perturbations	Task Assignment	Division of labor	One agent node can only be assigned to one task node
		Generalization of labor	One agent node can be assigned to multiple task nodes
	Decision-making Authority	Decentralized	Decision-making task nodes can be assigned to any agent nodes
		Centralized	Decision-making task nodes can only be assigned to certain agent nodes (i.e., manager level)
	Resource Management	Redundancy	Backup resource nodes exist
		No redundancy	No backup resource nodes

The first type of planning strategies is related to a project's level of exposure to uncertainty. These particular strategies affect the likelihood and perturbation impacts of uncertain events in a project's meta-network. For example, there are two alternative strategies for information processing and communication in construction projects: using computer-based information and communication technologies (ICTs), or using traditional communication tools (e.g., paper-based) (Arnold & Javernick-will, 2013). Adopting ICTs enhances the accuracy and efficiency of communication between different human agents in projects, and thus reduces the likelihood of occurrence of uncertain events caused by unclear or delayed information. When a project is less exposed to uncertain events, the likelihood and perturbation effects of uncertain events are reduced. Accordingly, project vulnerability is reduced as well.

The second type of planning strategies affect project vulnerability by influencing project sensitivity to uncertainty-induced perturbations. Planning strategies of this kind change the topological structure of project meta-networks by adding or removing nodes and/or links. For example, in construction projects, providing the right quantity of resources (i.e., neither excessive nor inadequate) is crucial in order to satisfy activity execution demand (Siu, Lu, & Abourizk, 2015). Thus, there are two alternative resource management strategies: either considering redundancy in resources, or not considering redundancy in resources. If redundancy in resources is adopted as a planning strategy in a project, additional resource nodes and corresponding links are added in the project meta-network. Those resource nodes serve as backup resources. In this case, if resource-related perturbations occur, the function of the project can be maintained by using the backup resources. In other words, the project is less sensitive to the exposure to resource-related perturbations. Reducing a project's sensitivity decreases its vulnerability to uncertainty as well.

In the proposed framework, project vulnerability is assessed under various planning strategy scenarios. To conduct the scenario analysis, a base scenario built on a combination of planning strategies is first developed. Comparative scenarios are then developed by changing the planning strategies of the base scenario in one or several aspects. Equation 4.11 is used to evaluate the effectiveness (u) of alternative planning strategies adopted in one comparative scenario in reducing project vulnerability:

$$u = \frac{v_B - v_c}{v_B} \tag{4.11}$$

where v_B denotes the vulnerability of a project to uncertainty in the base scenario, and v_c denotes the vulnerability of the same project in a comparative scenario.

4.3 Illustrative Case Study

The application of the proposed framework is shown through the use of a numerical case study related to a tunneling project. The objective of this numerical case is to demonstrate the application of the proposed framework and its potential significance. The tunneling project constructed using the New Austrian Tunneling Method (NATM) was analyzed. The case study information was mainly obtained from Ioannou and Martinez (1996). Additional information was obtained from other sources to supplement the information and resources used in the tunneling techniques. Compared to the conventional tunneling method, which uses the suspected worst rock condition for design, the NATM enables cost-saving by adjusting the initial design during the construction phase. In the NATM, rock samples are collected by the geologist team during the early stage of design. After conducting laboratory tests on the rock samples, the test results are compared with the rock quality designation index and the rock mass classification can be identified. The initial design is then conducted based on the identified rock type (Leca & Clough, 1992). The excavation crew performs excavation into the tunnel face based on the initial design, followed by loading explosives and blasting. Before blasting, the safety supervisor has to perform the safety inspection on the site and issue the safety approval. Right after the excavation work, the support installation crew starts working on the jobsite. The support installation crew applies shotcrete and installs the initial support (e.g., rockbolts, lattices girders or wire mesh) as the initial lining process. Measurement instruments are installed to observe the rock deformation behavior after the initial lining. The geologist team reads the data from the instruments and reports the rock deformation information to the designer team (Kontogianni & Stiros, 2005). The designer team then makes the decision on whether a revision on the initial design is needed. The decision depends on whether the rock deformation is within the acceptable range. If no revision is necessary, a final lining process composed of traditional reinforced concrete is conducted; otherwise, the designer team revises the initial design for both initial lining and final lining. In that case, the support installation crew will use the revised design to implement the initial and final lining (Kavvadas, 2005). The whole tunneling project is constructed in sections. At the end of each section, the project manager reviews the initial design and revised design, as well as the rock deformation, in order to makes a decision on the step length for excavation of the next section. For example, if a relatively large deformation is observed, the project manager will decrease the step length to prevent the chance of a collapse. Figure 4-4 summarizes the main process in the case study project.

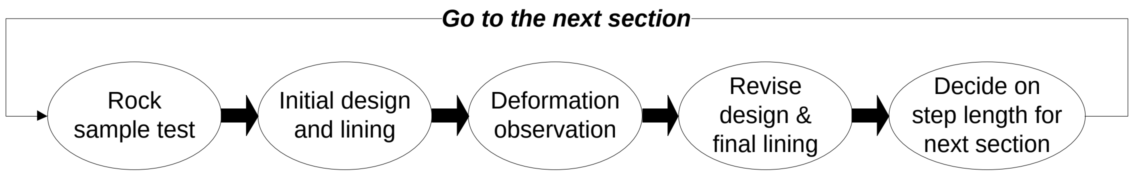


Figure 4-4 Processes of the Tunneling Project

4.3.1 Vulnerability assessment using the proposed framework

The proposed framework was used for analysis of vulnerability in the case study tunneling project. The four components of the proposed framework were conducted step-by-step in the context of the numerical example. ORA-NetScenes 3.0.9.9 was used as the network analysis and modeling platform (Carley, Pfeffer, Reminga, Storrick, & Columbus, 2013).

(1) Abstraction of Project Meta-network.

First, the meta-network of the tunneling project in the base scenario was abstracted. The base scenario of the project was developed from an initial selection of planning strategies (i.e., regular process in supplier selection, using traditional communication tools, generalization of labor, centralized decision-making authority, and non-redundancy in resource). To develop the project meta-network under the base scenario, the following steps were taken. First, task nodes were identified in the tunneling project (e.g., lab test, excavation, final lining). Second, the agents assigned for implementing the identified tasks were abstracted as agent nodes in the project meta-network (e.g., geologist team, designer team, excavation crew). Finally, information nodes (e.g., initial design, rock deformation) and resource nodes (e.g., concrete, support materials, excavator) were identified based on the requirement of different tasks. After identifying all the nodes, the links were built based on the relationships between different node entities. For example, the geologist team needs to report the rock data to the designer team. Thus, an agent to agent link was identified between the two agent nodes (i.e., geologist team and designer team). Designer team has access to the rock deformation data. Thus, an agent to information link was identified between the agent node and information node (i.e., designer team and rock deformation). In total, 36 nodes (of four different types) and 118 links (of ten different types) were abstracted in the tunneling project meta-network for the base scenario. Table 4-4 provides examples of different nodes and links in the project meta-network. Figure 4-5 shows the project meta-network.

Table 4-4 Examples of Nodes and Links in the Tunneling Project's Meta-network

	Types	Examples in the tunneling project case
Node	Agent (A)	geologist team, designer team, excavation crew, project manager, etc.
	Information (I)	rock condition, initial design, rock deformation, revised design, etc.
	Resource (R)	concrete, initial support materials, power system, excavator, etc.
	Task (T)	lab test, excavation, apply shotcrete, revise design, etc.
Link	A-A	geologist team reports to designer team
	A-I	designer team knows rock deformation
	A-R	geologist team uses measurement instrument
	A-T	designer team is assigned to conduct initial and revised design
	I-I	revised design information depends on rock deformation
	I-R	initial design is needed for choosing initial support materials
	I-T	rock deformation is needed for deciding step length
	R-R	concrete is used by shotcrete machine
	R-T	loader and trucks are needed for mucking
	T-T	safety inspection is conducted before blasting

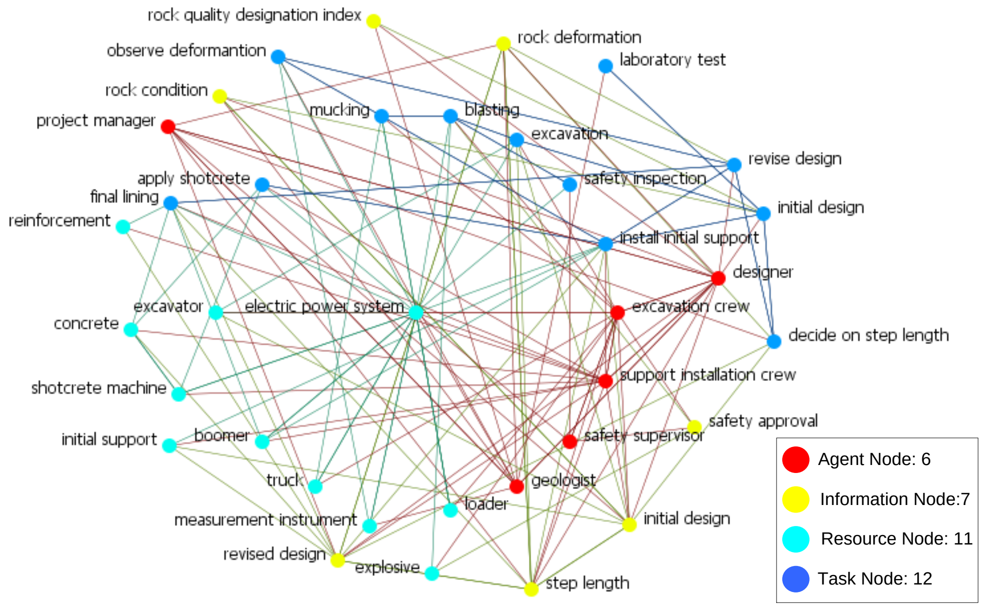


Figure 4-5 Tunneling Project Meta-network in Base Scenario

(2) Translation of Uncertainty.

Based on past research on construction risk factors (e.g., Choudhry et al., 2014; El-Sayegh, 2008; Zou et al., 2007), multiple uncertain events related to agents, information, and resources were identified in the context of the tunneling project. In the project's uncertain environment (E), 30 possible uncertain events (n) were identified. Table 4-5 shows examples of the identified uncertain events (e), their likelihoods of occurrence (L), and perturbation effects (PE) in the tunneling project. The likelihoods were defined at three levels as low, medium, and high, each with a 10%, 20% and 50% likelihood to occur (Abdelgawad & Fayek, 2010). The perturbation effects were generated from the impacts of the events on the project meta-network. For example, uncertain event "limited access to rock deformation information" has a medium likelihood of occurrence and an information-related perturbation effect. It means that there is a 20% likelihood that the information of rock deformation cannot be delivered in time to the designers and project manager in the project. The occurrence of this event will have a perturbation effect of removing links between the rock deformation information node and agent nodes in the project meta-network. Each of these uncertain events was defined as an independent, random event based on its likelihood of occurrence. Thus, in the tunneling project, any combination of these 30 uncertain events could happen and randomly cause perturbations in the project, based on their likelihoods.

Table 4-5 Examples of Uncertain Events in the Tunneling Project

Uncertain Events (e)	Likelihood (L)	Perturbation Effect (PE)
Geologist dereliction of duty	Medium (20%)	Agent-related perturbation in geologist
Designer staff turnover	Low (10%)	Agent-related perturbation in designer
Limited Access to rock deformation information	Medium (20%)	Information-related perturbation in rock deformation
Excavator breakdown	Medium (20%)	Resource-relation perturbation in excavator
Late delivery of concrete	High (50%)	Resource-related perturbation in concrete
Power system failure	Medium (20%)	Resource-related perturbations in multiple pieces of equipment
Severe weather	Low (10%)	Multiple agent-related and resource-related perturbations
Economic fluctuation	Low (10%)	Multiple agent-related and resource-related perturbations

(3) Quantification of Project Vulnerability.

Two sets of analyses related to project vulnerability quantification were conducted in the tunneling project case: (1) identifying critical node entities, and (2) assessing project vulnerability. The purpose of the first set of analysis was to identify the critical agent, information, and resource nodes in the project. For achieving this purpose, project vulnerability was assessed against uncertain events related to single perturbations in each node respectively (e.g., designer team turnover, late delivery of concrete, miscommunication on revised design information). When the project shows a high level of vulnerability against perturbations in specific nodes, those nodes can be identified as critical in the project meta-network.

In the tunneling project case, 24 experiments were conduct in total to obtain the project vulnerability under perturbations related to each agent, information, and resource node. In each vulnerability assessment experiment, the likelihood of occurrence of one uncertain event was set to 1, and the likelihoods of occurrence of all the other uncertain events in the uncertain environment (E) were set to 0. After conducting the project vulnerability assessment experiments, the most critical agent, information, and resource nodes in the tunneling project case were identified (Figure 4-6). For example, as shown in Fig. 6, the electric power system is identified as the most critical resource node in the project. The project vulnerability is 0.333 (i.e., project meta-network efficiency decreases from 1 to 0.667) when a perturbation in the electric power system node occurs, which indicates that 33.3% of project tasks are affected in this circumstance. The electric power system is critical in the tunneling project because it is used by the geologist team, excavation crew and support installation crew in multiple tasks such as excavation, safety inspection, and rock deformation observation. The critical nodes identified in the tunneling project are often connected to more nodes and have significant contribution to task completion in the project meta-network. Identifying critical agents, information, and resources during the project planning phase provides important insight for decision makers to better plan and manage their projects. For example, by knowing who the critical agents are, decision makers can consider reliability as an important factor in selecting crews or individuals for the critical agent nodes. By knowing what the critical information is, decision makers can prioritize the processing requests to make sure the critical information can be delivered accurately and in time. By knowing what the critical resource are, decision makers can develop corresponding plans (e.g., pre-ordering of materials, preparing backup power system) to ensure the availability and proper functionality of critical resources in projects.

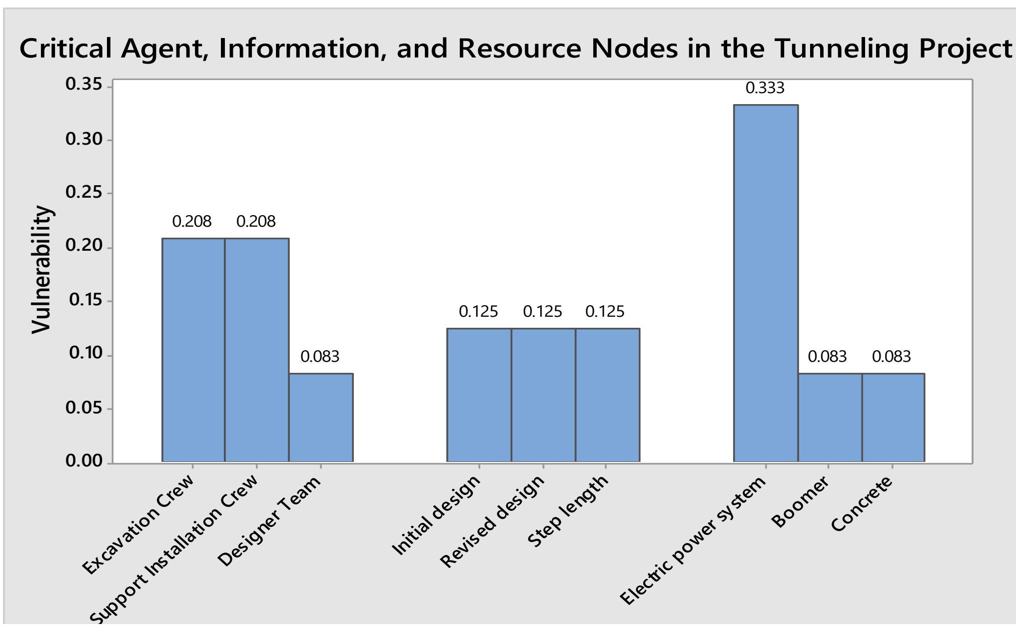


Figure 4-6 Critical Agent, Information, and Resource Nodes in Tunneling Project

The purpose of the second set of analysis was to assess the level of project vulnerability under the uncertain environment. Monte Carlo simulation was used to model the randomness in the occurrence of the uncertain events by conducting multiple runs of vulnerability assessment (Rubenstein & Kroese, 2011). In each run of the Monte Carlo experiment, different combinations of random uncertain events happened based on their likelihood of occurrence. Figure 4-7 shows the result of one run of Monte Carlo experiment. In this experiment run, several uncertain events happened simultaneously. The safety supervisor left the position and the geologist team was not performing its duties in the project. The information related to rock deformation was not available for timely use. There were delays in the delivery of materials to the jobsite, including explosives, initial support materials, and concrete. Finally, the boomer, which is a versatile machine facilitating the task of support installation, didn't function properly during the project. In this specific circumstance, the project meta-network was pushed away from its original state, as shown in Figure 4-7. Two nodes (i.e., agent nodes of the safety supervisor and the geologist team) and 19 links (e.g., the link between rock deformation information and designer team and the link between boomer and support installation crew) were removed from the project meta-network. The network efficiency was decreased from 1 to 0.667, which means after the perturbations, only 66.7% of the tasks could be completed if no adaptive or restorative actions were taken. Thus, the project vulnerability to the uncertain events evaluated in this run is 0.333.

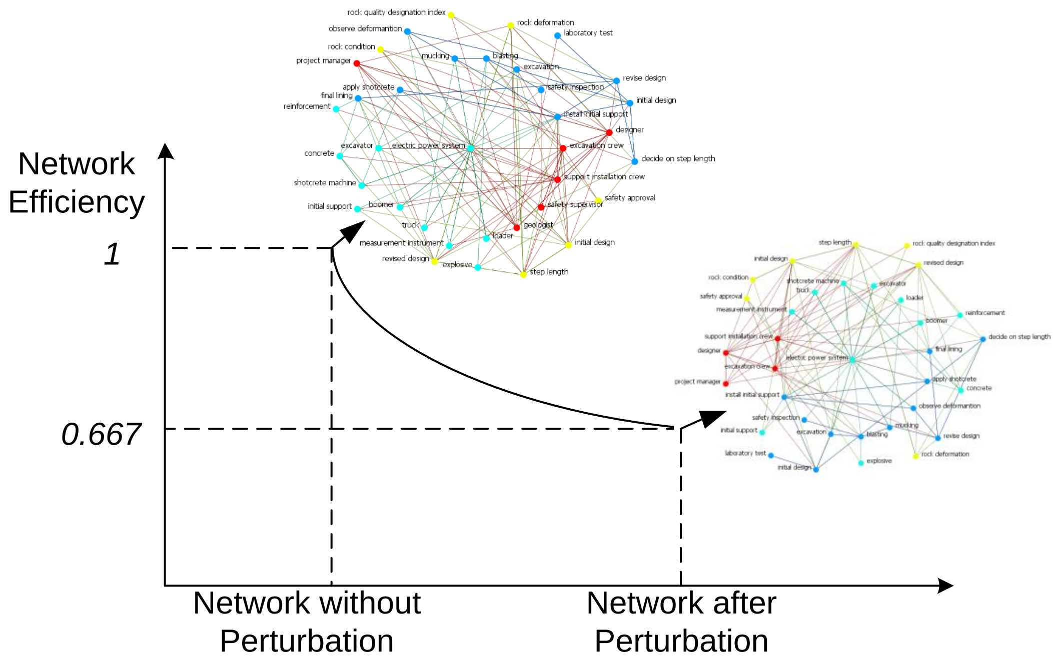


Figure 4-7 Vulnerability Assessment in One Run of Monte Carlo Experiment

In total, 100 runs of Monte Carlo experiment were conducted. Figure 4-8 and Figure 4-9 show the results of vulnerability assessment in the total 100 runs of the Monte Carlo experiments for the base scenario. Figure 4-8 is a boxplot for the values of project vulnerability in different runs. Each data point shows the vulnerability obtained in one run. The interquartile range box indicates that 25% of the vulnerability values in the 100 runs are less than 0.29, and 75% of them are less than 0.49. Figure 4-9 also suggests that the vulnerability values obtained in the 100 runs are normally distributed. Figure 4-9 shows the bell curve of the distribution. With a mean value (0.39) and standard deviation (0.116) of the 100 samples, the average vulnerability of the tunneling project to the uncertain environment (E) can be predicted. For example, with a 95% confidence interval, the average vulnerability value of the tunneling project under the base scenario is between 0.371 and 0.417.

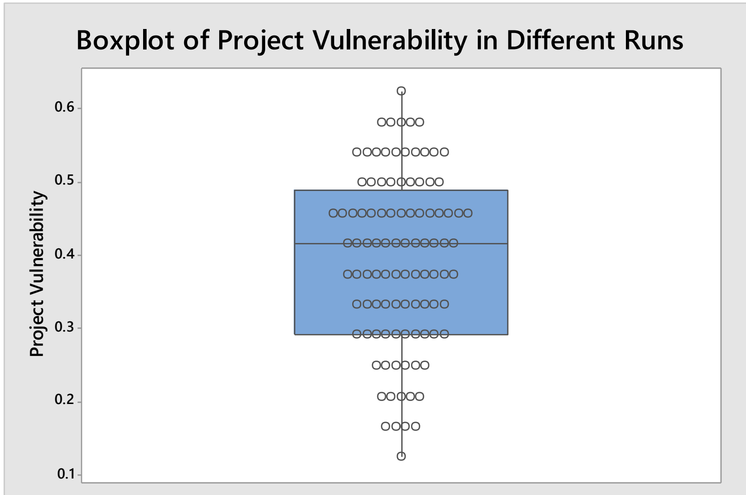


Figure 4-8 Boxplot of Project Vulnerability Simulation Results

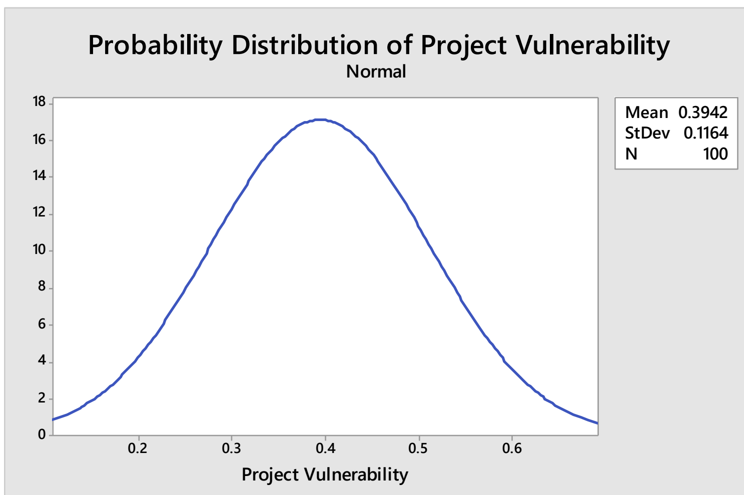


Figure 4-9 Project Vulnerability Simulation Results in Normal Distribution

A higher level of vulnerability implies greater losses of project performance in uncertain environments. Thus the quantified project vulnerability value can be used as a leading indicator in project performance assessment. Before each construction project starts, project management and control team can conduct ex-ante project vulnerability assessment based on the project characteristics and project environment. If the level of vulnerability assessed is higher than the trigger point (for example 20%) set by the project management and control team, the project team should consider additional vulnerability mitigation strategies. Otherwise, project performance variation due to uncertainty may go beyond the acceptable level and causes negative effects on the project.

(4) Evaluation of Planning Strategies.

To evaluate different planning strategies, five comparative scenarios (i.e., C1-C5) composed of different planning strategies were considered. For each comparative scenario, only one aspect of planning strategies was changed from the base scenario (Table 4-6). Figure 4-10 shows the impacts of the changes in planning strategies on the meta-network of the tunneling project in the five comparative scenarios.

Table 4-6 Planning Strategies Adopted in Comparative Scenarios

Types of Planning Strategies	Planning Strategies		BS	C1	C2	C3	C4	C5
Exposure to Uncertainty	Supplier Selection	Prequalification		√				
		Regular selection process	√		√	√	√	√
	Information Processing and Communication	ICTs			√			
		Traditional Tools	√	√		√	√	√
Sensitivity to Uncertainty-induced Perturbations	Task Assignment	Division of labor				√		
		Generalization of labor	√	√	√		√	√
	Decision-making Authority	Decentralized					√	
		Centralized	√	√	√	√		√
	Resource Management	Redundancy						√
		No redundancy	√	√	√	√	√	

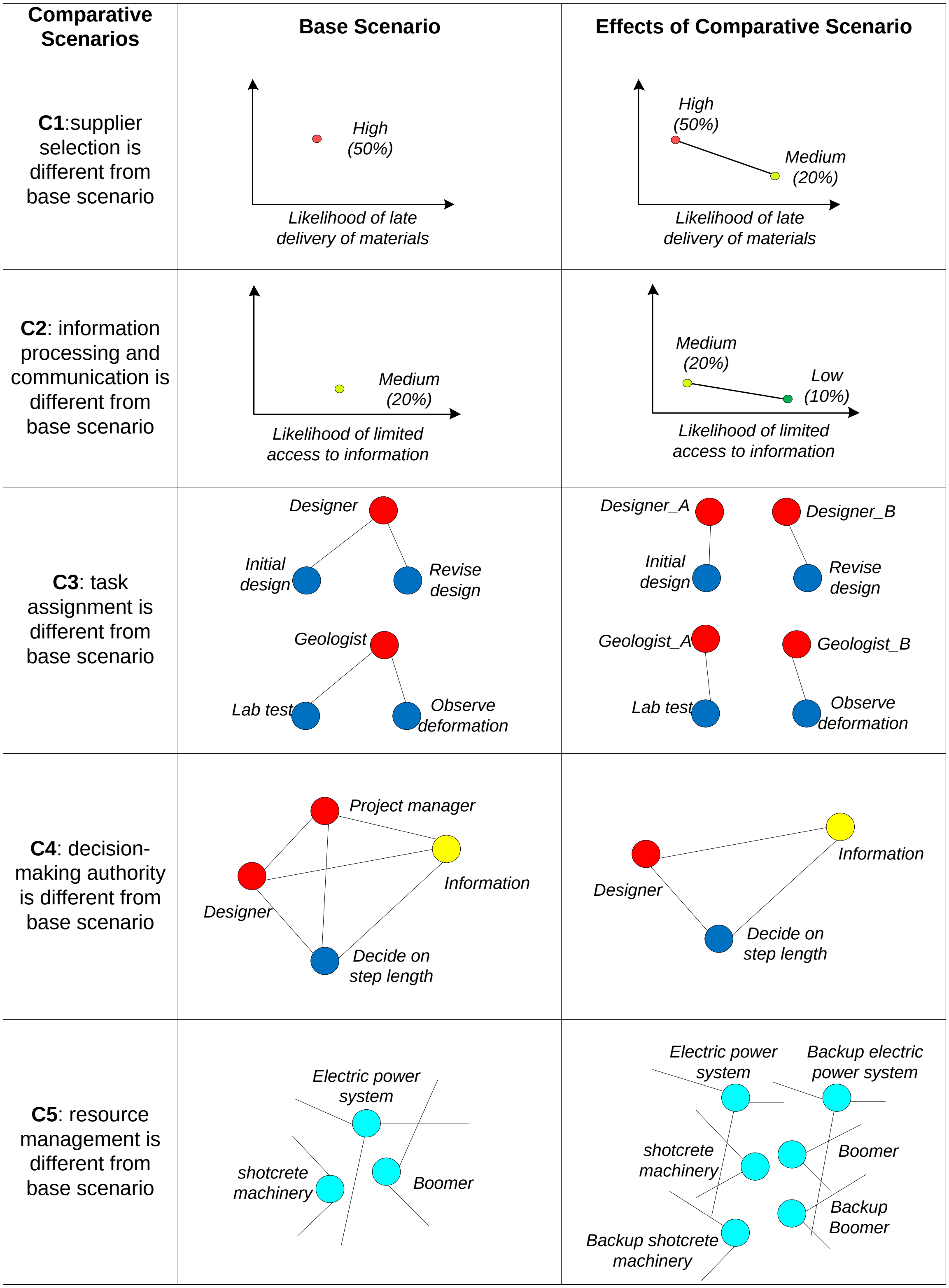
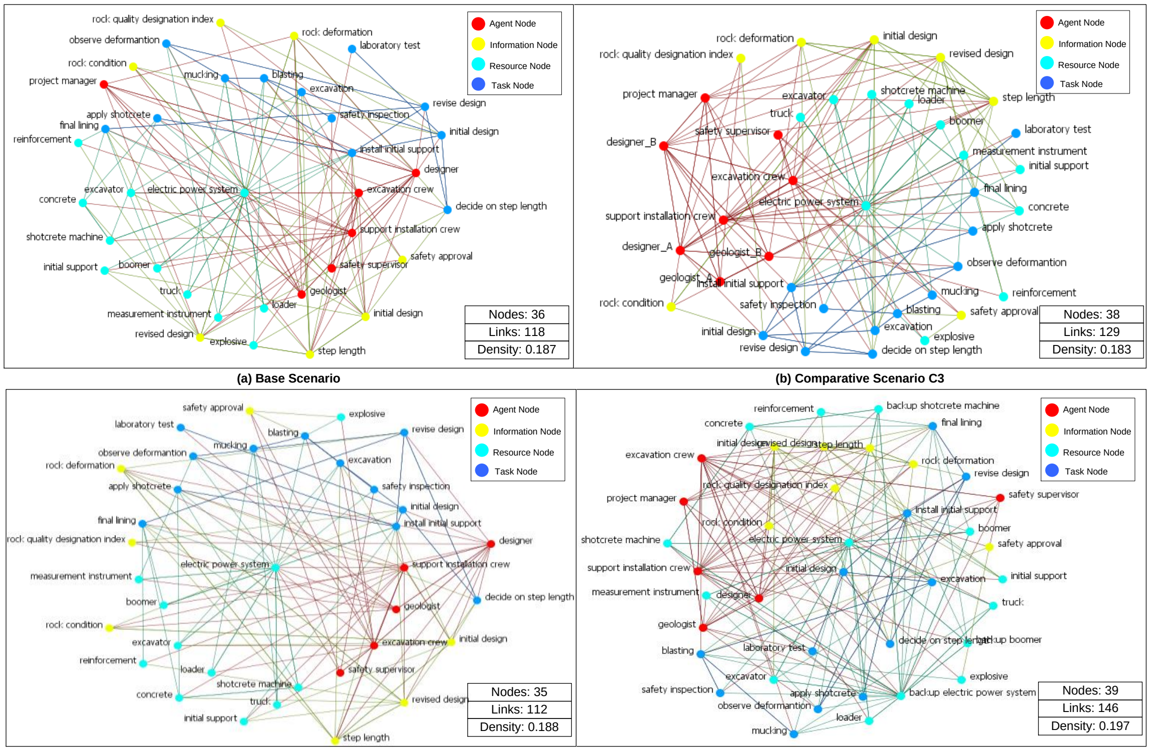


Figure 4-10 Effects of Planning Strategies in Comparative Scenarios

Comparative scenarios C1 and C2 adopted alternative planning strategies which may affect project vulnerability by influencing a project's exposure to uncertainty. In comparative scenario C1, the planning strategy related to supplier selection was changed from "regular selection process" to "prequalification of suppliers." Prequalification helped to identify the best qualified supplier, thus reducing the likelihood of uncertain events related to late delivery of materials in the tunneling project from "high" to "medium". In comparative scenario C2, the planning strategy related to information processing and communication was changed from "using traditional tools" to "using ICTs". As a result, the likelihood of uncertain events related to limited access to information in the tunneling project was reduced from "medium" to "low".

Comparative scenarios C3, C4, and C5 were related to planning strategies which may affect project vulnerability by influencing the sensitivity of a project to uncertainty-induced perturbations. In comparative scenario C3, the planning strategy related to task assigned was changed from "generalization of labor" to "division of labor". In the base scenario, the tasks were assigned based on "generalization of labor", and thus one geologist team was assigned for both tasks of conducting laboratory tests and observing rock deformation. Similarly, one designer team was assigned for both tasks of conducting initial design and revised design. When "division of labor" was adopted in comparative scenario C3, two more agent nodes were added as additional geologist team and designer team. Tasks of laboratory tests and observing rock deformation were assigned to the two geologist teams respectively, and so were the tasks related to design. In comparative scenario C4, the planning strategy pertaining to decision-making authority was changed from "centralized" in the base scenario to "decentralized". In the base scenario, the designer team should report the corresponding information (e.g., initial design, revised design and rock deformation) to the project manager and wait for the project manager to make the decision on the step length for the next section. In comparative scenario C4, the decision-making authority related to step length was given to the designer team, since the designer team already had all the required information for making the decision. Thus, in comparative scenario C4, the project manager node and its corresponding links were removed. In comparative scenario C5, the planning strategy for resource management was changed from “no redundancy” to “redundancy in resource”. Additional nodes of electric power system, shotcrete machinery, and boomer were added as backup resources. Backup resource nodes were linked to other corresponding nodes in the project meta-network so that they could be used when the original resources were not functioning due to uncertain events. In these three comparative scenarios, the topological structure of the project meta-network was changed by adding or removing nodes and/or links. Figure 4-11 shows the project meta-networks under the base scenario and comparative scenarios C3-C5. As shown in Figure 4-11, project meta-networks under different scenarios have different numbers of nodes, links, as well as network densities.

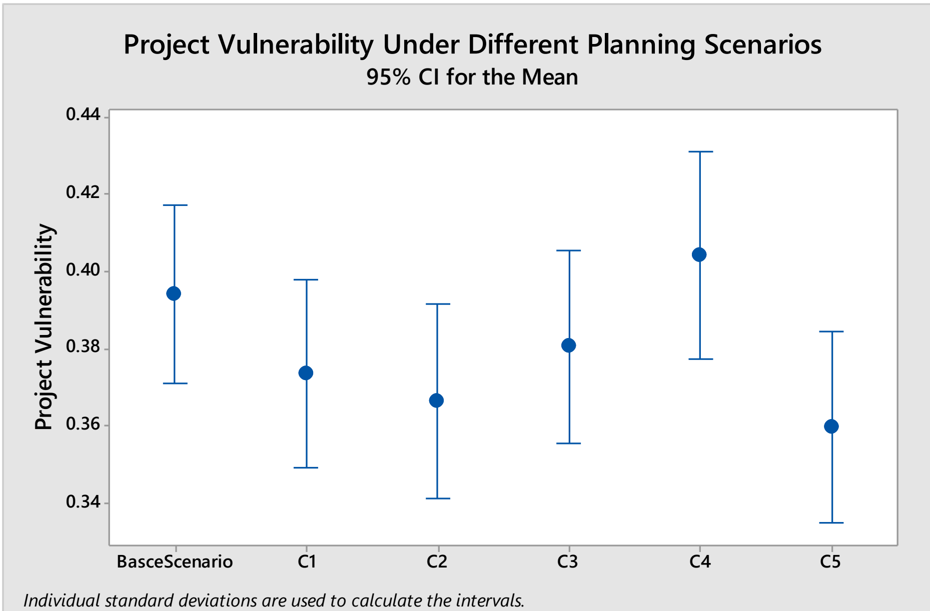


(a) Base Scenario (b) Comparative Scenario C3

(c) Comparative Scenario C4 (d) Comparative Scenario C5

Figure 4-11 Meta-networks of the Tunneling Project under Different Scenarios

For each of the five comparative scenarios, vulnerability assessment was conducted using Monte Carlo simulation and the distributions of project vulnerability under all the five scenarios were obtained. The effectiveness of planning strategies adopted in the comparative scenarios was then evaluated based on its effect in reducing the average project vulnerability. Figure 4-12 shows the results of the vulnerability assessment in the base scenario, as well as the five comparative scenarios. The interval plots in Figure 4-12 depict the mean values of 100 runs of the Monte Carlo experiments for each scenario with a 95% confidence interval. The effectiveness of each mitigation strategy (u) was evaluated by its effect in reducing the mean value of project vulnerability using Equation 4.11 introduced before in the framework. From the results shown in Figure 4-12, the planning strategy of "redundancy in resource", as adopted in comparative scenario C5, is the most effective strategy because it decreased the vulnerability of the tunneling project in the base scenario by 8.80%. Since the backup resources could help to maintain the efficiency of the project network, the project becomes more robust, especially against resource-related perturbations. The planning strategy of using ICTs in comparative scenario C2 also shows the capability of reducing vulnerability in the tunneling project. Using ICTs can reduce the likelihood of miscommunication or limited access to information in the project. Compared with the base scenario of the tunneling project, in which conventional communication tools are used, the mean value of the vulnerability assessed in the samples of comparative scenario C2 is reduced by 7.08%. “Prequalification of suppliers” adopted in comparative scenario C1 is identified as another useful strategy in mitigating the vulnerability of the tunneling project by reducing the exposure to resource-related uncertainty. In this tunneling project, this strategy decreases the vulnerability of the project in the base scenario by 5.30%. The other two planning strategies considered in comparative scenario C3 and C4: “division of labor” and “decentralized decision-making authority”, however, do not show significant impact on mitigating vulnerability in the tunneling project. When adopting “division of labor” as the planning strategy of task assignment, the average project vulnerability only decreases by 3.50% compared to the base scenario. When adopting “decentralized decision-making authority” as the planning strategy, the average project vulnerability actually increases compared to the base scenario. The result suggests that, in the tunneling project, “centralized decision-making authority” adopted in the base scenario may be a better planning strategy for minimizing the level of project vulnerability. Hence, in this tunneling project, “redundancy in resource”, “using ICTs”, and “prequalification of suppliers” are the most effective planning strategies for mitigating vulnerability in the project.



	N	Mean	StDev	95% CI	Effectiveness (u)
Base Scenario	100	0.3942	0.1164	(0.3711, 0.4173)	-
Comparative Scenario C1	100	0.3733	0.1230	(0.3489, 0.3977)	5.30%
Comparative Scenario C2	100	0.3663	0.1274	(0.3410, 0.3915)	7.08%
Comparative Scenario C3	100	0.3804	0.1260	(0.3554, 0.4054)	3.50%
Comparative Scenario C4	100	0.4041	0.1359	(0.3771, 0.4311)	-2.51%
Comparative Scenario C5	100	0.3595	0.1251	(0.3347, 0.3844)	8.80%

Figure 4-12 Effectiveness of Planning Strategies in the Tunneling Project

The information obtained from evaluation of planning strategies can help decision makers to design less vulnerable construction projects. In the construction industry, project teams may be reluctant to adopt proactive strategies in order to reduce the impact of uncertainty, since adopting those strategies usually implies more investment (e.g., hiring more agents, ordering backup resources, purchasing information systems) and the effectiveness of these proactive measures are hard to quantify. However, through the use of the proposed framework, decision makers in construction projects can quantify and compare the effectiveness of alternative planning strategies in order to justify proactive measures for mitigating vulnerability during project planning.

The verification and validation of the illustrative numerical case study was conducted. First, various nodes and links as input to the simulation model were evaluated by two individuals separately through a face validation process to ensure that the meta-network captures the human agents, information, resources, tasks and their relationships in the illustrative case study. Second, the meta-network simulation model was validated using different validation techniques such as internal validity and extreme condition test (Sargent, 2011). For example, in one of the extreme condition tests, all the human agent nodes were intentionally removed in the tunneling project meta-network, and the simulation result of the network efficiency was decreased to 0. The outcomes of the validation signified the logic and input-output relationships in the simulation model were correct. Since this case study was an illustrative example for demonstration of application, external validation of results was not applicable.

The results from the illustrative numerical case presented highlighted the potential and significance of the proposed meta-network framework in: (1) identifying the critical human agent, information, and resource entities; (2) quantifying the project overall vulnerability to uncertainty; (3) evaluating the effectiveness of different planning strategies in mitigating vulnerability in the tunneling project. The general applicability of these findings (e.g., the effectiveness of redundancy in resource in mitigating project vulnerability) need to be further tested and compared across different cases in future studies.

4.4 Conclusions

This paper presented a new framework for conceptualization and quantitative assessment of vulnerability to uncertainty in construction projects. The proposed framework advances theoretical and methodological approaches for assessment of performance and uncertainty in projects in various areas. First, from a theoretical perspective, the proposed framework introduces project vulnerability as an important phenomenon in assessment of the impact of uncertainty on project performance. The conventional uncertainty assessment approaches in construction research and project management literature mainly focus on identification of risk factors and fail to consider project vulnerability. In the proposed framework, project vulnerability has been conceptualized as an important aspect in evaluation project performance under uncertainty. Conceptualization and analysis of project vulnerability advances the existing knowledge toward better understanding of factors affecting and ways to mitigate the impacts of uncertainty on project performance. Such understanding is essential in order to enhance the performance of construction projects. Second, the proposed framework enables abstraction and analysis of various entities and interactions in assessment of performance and uncertainty in construction projects. The fundamental premise of the proposed framework is that construction projects are meta-networks composed of interconnected agent, information, resources, and task nodes. Such conceptualization enables capturing dynamic interactions affecting the performance of construction projects. Hence, it enables an integrated assessment of the different dimensions of performance management in construction projects (e.g., project planning, interface management, and organizational design). Third, the framework presented in this study advances the existing computational approaches in civil engineering by providing a methodology to simulate the impacts of uncertainty on projects' meta-networks. The proposed framework integrates elements from complex systems, dynamic network analysis, and Monte Carlo simulation approaches in order to predictively evaluate vulnerability to uncertainty in projects. Hence, the proposed framework provides means for predictive assessment and proactive mitigation of vulnerability to uncertainty in civil engineering projects using a computational approach. These theoretical contributions can ultimately lead to an integrated theory towards a proactive, predictive, and quantitative paradigm in assessment of performance and uncertainty in construction projects.

From a practical perspective, the proposed framework enables: (1) identifying of the critical agents, information and resources in projects based on vulnerability assessment to single-node perturbations; (2) assessing the overall level of project vulnerability in uncertain environments; and (3) evaluating project planning strategies in terms of their effectiveness in reducing vulnerability of construction projects. Project managers can use the information obtained from project vulnerability assessment for: (1) forecasting possible disturbances in project performance based on assessment of project vulnerability; (2) designing less vulnerable and more robust projects by selecting and adopting effective project planning strategies; (3) developing project management plans in order to reinforce the critical agent, information, and resource nodes.

The framework proposed in this paper has some limitations. First, in the current framework, impacts of uncertain events on project tasks are conceptualized as removal of affected nodes and/or links in the network. Thus, a certain task is either "successfully completed" or "not successfully completed" based on the availability of the required human agents, information and resources. However, in reality, uncertain events may have partial impacts on the links and nodes of a project meta-network. Also, some of the tasks may be partially completed in the absence of required agents, resources, and information. To capture these partial impacts, the links in the meta-network can be weighted and the impacts of uncertainty-induced perturbations on task completion can be modeled based on changes in the weights of the links. This addition is part of the future work of the authors in this study. Another limitation in the proposed framework is that all tasks in a construction project have the same importance weight in calculating the percentage of task completion as the indicator for network efficiency. However, in reality, different tasks may have different levels of importance. The failure to successfully completing different tasks may have varying degrees of impacts on a project performance. As a future study, the authors will refine the meta-network framework by taking different importance weights of tasks into consideration.

The implementation of the proposed meta-network framework has some limitations as well. The implementation of the proposed meta-network framework requires a certain level of knowledge and skills from the users, such as knowledge to the many inputs (i.e., human agents, information, resources, and tasks) of the meta-network in a specific project, ability in abstraction and conceptualization, as well as modeling skills. Currently, the best way to implement the proposed meta-network is to ask practitioners to work with researchers who have knowledge in network modeling. Frequent discussions and face validations between practitioners and researchers can ensure the meta-network model and analysis capture the important aspects of a project meta-network.

5. PROJECT VULNERABILITY, ADAPTIVE CAPACITY, AND RESILIENCE UNDER UNCERTAIN ENVIRONMENTS

This chapter presents the overall framework for integrated assessment of project vulnerability, adaptive capacity and resilience to uncertainty. In the proposed framework, construction projects are conceptualized as meta-networks composed of different types of nodes (i.e., agents, information, resources, and tasks) and links representing interdependencies between these node entities. The impacts of uncertain events on construction projects are translated as perturbations in different nodes and/or links in project meta-networks. The uncertainty-induced perturbations cause decreases in project meta-network efficiency, and ultimately cause project performance deviations. In this research, project schedule deviation under uncertainty is selected as the measure of project resilience to uncertainty. Project resilience is investigated based on two properties: (1) project vulnerability (i.e., the decrease in meta-network efficiency under uncertainty-induced perturbations); and (2) project adaptive capacity (i.e., the speed and capability to recover from uncertainty-induced perturbations). Different project planning strategies are evaluated based on their effectiveness in mitigating the negative impacts of uncertainty by reducing project vulnerability or enhancing project adaptive capacity. The application of the proposed framework is demonstrated in 3 case studies from complex commercial building projects. Different scenarios related to uncertain events and planning strategies were simulated in the case studies. The results of the case studies show the capability of the proposed dynamic meta-network modeling framework in: (1) quantitative and predictive evaluation of the impacts of uncertainty on project performance; (2) ex-ante evaluation of the effectiveness of planning strategies in mitigating the negative impacts of uncertainty on project performance; and (3) capturing the complex interactions between various tasks, agents, information, and resources in evaluation of project performance under uncertainty. The simulation results reveal the relationships between project vulnerability, adaptive capacity, resilience and project performance outcomes under uncertainty.

5.1 Introduction

Performance inefficiency such as cost overrun and time delay continues to be a major concern in the construction industry. One of the major reasons of the unpredictability of construction project performance is the high level of uncertainty in modern construction projects. Despite a growing body of literature in the areas of performance assessment and uncertainty analysis in construction projects, the understanding of the dynamic behaviors and performance outcomes in complex construction projects under uncertainty remains limited. First, the existing studies (e.g., El-Sayegh, 2008; Zou et al., 2007) in construction project performance assessment under uncertainty are mainly subjective in nature and focus on identification and evaluation of risk factors. These studies do not provide a robust quantitative basis for predictive performance assessment in construction projects. Second, the existing studies do not capture the dynamic interactions and interdependencies between various entities in the assessment of performance under uncertainty in construction projects. Construction projects are complex systems composed of interconnected entities (i.e., human agents, information, resources, and tasks) (Zhu & Mostafavi, 2014c). A better understanding of the behaviors of construction projects under uncertainty is contingent on capturing and analyzing the dynamic interdependencies between various entities. Third, the existing approaches in assessment of performance under uncertainty in construction are reactive in nature. A more proactive approach that requires evaluation of planning strategies in terms of their effectiveness in mitigating the negative impacts of uncertainty during project planning phase is missing. To address these methodological limitations and gaps in knowledge, a dynamic meta-network modeling framework is proposed in this study. In the proposed framework, construction projects are conceptualized as dynamic multi-node and multi-link meta-networks composed of different node entities (i.e., agents, information, resources and tasks) and their interdependencies. The uncertain events in construction projects are translated into perturbations in the node entities and/or links of project meta-networks. The impacts of uncertainty-induced perturbations on the performance of projects are assessed using stochastic simulation. Important project properties (e.g., project vulnerability and adaptive capacity) affecting the impacts of uncertainty on project performance are investigated in evaluation of project performance under uncertainty. Accordingly, planning strategies are evaluated based on their effectiveness in mitigating the impacts of uncertainty on project performance.

5.2 Framework for Resilience Assessment in Project Systems

The proposed framework for resilience assessment in project systems includes six components: (1) abstraction of project meta-networks; (2) translation of uncertainty into perturbations in the meta-network nodes and links; (3) quantification of project vulnerability; (4) determination of project adaptive capacity; (5) assessment of performance deviation; and (6) evaluation of planning strategies. Figure 5-1 depicts the linkages between different components.

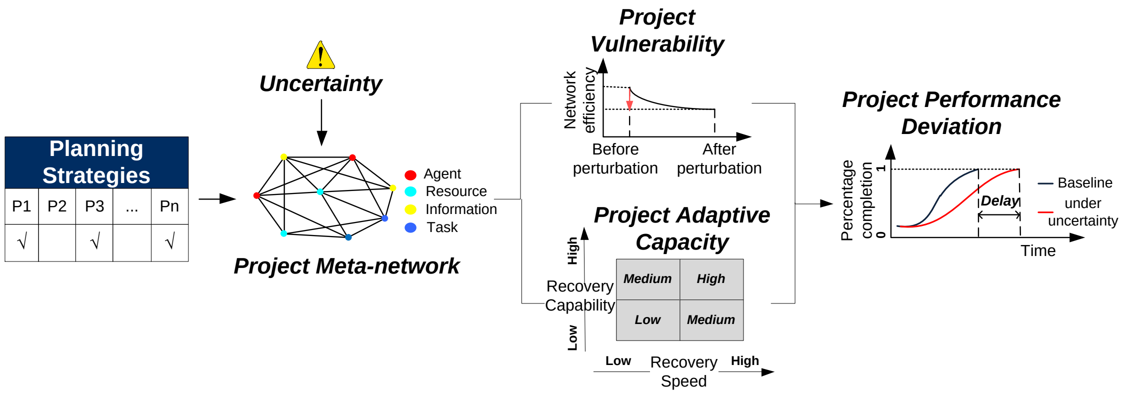


Figure 5-1 Linkages between Different Components in the Proposed Framework

5.2.1 Abstraction of project meta-networks

In the proposed framework, construction projects are conceptualized as interconnected and heterogeneous meta-networks composed of four types of entities: human agents, information, resources, and tasks (Zhu & Mostafavi, 2015a). The complex interactions and interdependencies between different entities in a project can be captured as different types of links in the project meta-network (e.g., who works with who, who knows what, who is assigned to what task, what resource is needed for what task, what information is needed for what task). This conceptualization is based on abstraction and evaluation of projects at the base-level in which human agents utilize information and resources to implement different tasks (Zhu & Mostafavi, 2014c). To abstract the node entities and their interconnections in a project, the first step is to identify the task nodes. In construction projects, a task node could represent decision making, information processing or production work. After identification of the task nodes, the agent nodes can be identified. An agent node is an entity that implements the task. It could be an individual, a crew, or a team depending on the nature of tasks. Then, information and resource nodes can be identified accordingly based on the requirements of tasks. The interdependencies and relationships between different node entities build the links in a project meta-network. Each type of links represents one type of relationship (e.g., agent-information link represents who knows what, agent-task link represents who is assigned to what task).

5.2.2 Translation of uncertainty

In the proposed framework, the effects of uncertainty in construction projects are translated into uncertain-induced perturbations. The perturbations are modeled through removal of nodes and links in project meta-networks (Zhu & Mostafavi, 2015a). The perturbation effects can be captured by two components: (1) the nodes and links removed; and (2) the duration of the removal. There are three basic types of perturbation effects based on the nodes and links removed due to uncertain events. They are: (1) agent-related, (2) information-related, and (3) resource-related. For example, agent-related perturbation effects cause removal of certain agent nodes and corresponding links. Examples of uncertain events which lead to agent-related perturbation effects include staff turnover and dereliction of duty. Each type of perturbation, based on the magnitude of the perturbation effects (i.e., duration of the removal of nodes and links), can be further defined at three different levels: (1) high-disturbance perturbation, (2) medium-disturbance perturbation, and (3) low-disturbance perturbation. A high-disturbance perturbation effect will lead to a longer duration of removal of certain nodes and links. For instance, both key staff turnover and regular staff turnover cause agent-related perturbations in project meta-networks. However, the turnover of key staff (e.g., project manager) has a more significant impact on projects. It leads to a longer duration of removal of the agent nodes representing key staff, since it is usually more difficult to eliminate the perturbation effects by finding replacement of the key personnel. Thus, the turnover of key staff (e.g., project manager) leads to a high-disturbance agent-related perturbation effect, while the turnover of regular staff leads to a low-disturbance agent-related perturbation effect. Based on the perturbation type and level of disturbance, uncertain events can be categorized as nine different categories. Table 5-1 shows these nine categories and examples of uncertain events in those categories.

Table 5-1 Examples of Uncertain Events as Sources of Perturbations.

Perturbation Type	Perturbation Level	Examples of uncertain events
Agent-related	High-disturbance	Safety accident or injury, key staff turnover, dereliction of duty
	Medium-disturbance	Shortage of manpower
	Low-disturbance	Regular staff turnover
Information-related	High-disturbance	Delay in processing key information, inaccurate design
	Medium-disturbance	Limited access to required information, miscommunication
	Low-disturbance	unclear scope/design
Resource-related	High-disturbance	Power supply issue
	Medium-disturbance	Defective material, single equipment breakdown
	Low-disturbance	Late delivery of material

At the meta-network level, the perturbations cause topological changes in a project meta-network, and thus, lead to decreases in the meta-network efficiency. The decrease in network efficiency is only affected by the nature of uncertain events. At the task-level, the perturbations cause delays in implementation of certain tasks, since the successful implementation of each task in a project meta-network depends on the availability of corresponding human agents, information, and resources. The amount of delay in tasks is determined by the perturbation effects as well as the level of adaptive capacity in different project systems. More details on project adaptive capacity and its impact on project meta-networks will be explained in section 5.2.4.

In the proposed framework, the uncertain environment in which a project system operates can be modeled by the likelihood of occurrence of each category of uncertain events and their perturbation effects. The likelihood means at a given period of time (e.g., one day), out of all the required human agents, resources, or information, the percentage of them that would experience high-disturbance, medium-disturbance, or low-disturbance uncertain events. In this study, three levels of likelihood were defined as: (1) high (20%), (2) medium (10%), and (3) low (5%). The likelihood of each category of uncertain events was then captured through interview and coding techniques. For example, if the likelihood of medium-disturbance resource-related uncertain events is high in a specific project system according to interview, it means on each day, 20% of the resources used would encounter medium-disturbance uncertain events such as defective material or equipment breakdown. The overall human-related (U_h), information-related (U_i) and resource-related (U_r) uncertainty can be calculated using equations below:

$$U_h = 1 - (1 - U_{hh})(1 - U_{hm})(1 - U_{hl}) \tag{5.1}$$

where U_{hh} is the likelihood of high-disturbance human-related uncertain events, U_{hm} is the likelihood of medium-disturbance human-related uncertain events, U_{hl} is the likelihood of low-disturbance human-related uncertain events.

$$U_i = 1 - (1 - U_{ih})(1 - U_{im})(1 - U_{il}) \tag{5.2}$$

where U_{ih} is the likelihood of high-disturbance information-related uncertain events, U_{im} is the likelihood of medium-disturbance information-related uncertain events, U_{il} is the likelihood of low-disturbance information-related uncertain events.

$$U_r = 1 - (1 - U_{rh})(1 - U_{rm})(1 - U_{rl}) \tag{5.3}$$

where U_{rh} is the likelihood of high-disturbance resource-related uncertain events, U_{rm} is the likelihood of medium-disturbance resource-related uncertain events, U_{rl} is the likelihood of low-disturbance resource-related uncertain events.

5.2.3 Quantification of project vulnerability

Project vulnerability is determined based on the magnitude of changes in the efficiency of a project meta-network due to uncertainty-induced perturbations (Criado et al., 2005). In the proposed framework, vulnerability is measured based on the reduction in the percentage of tasks that can be completed by the agent assigned to them, based on whether the agents have the requisite information and resources to do the tasks (Carley & Reminga, 2004). More details on the calculation of project vulnerability can be found in Zhu & Mostafavi (2015b). The value of project vulnerability ranges from 0 to 1. A greater value of vulnerability indicates that a project is more vulnerable, and thus, is more likely to experience a greater extent of negative impacts due to uncertainty-induced perturbations.

5.2.4 Determination of project adaptive capacity

Project adaptive capacity is determined based on the speed and capability of a project meta-network to recover from uncertainty-induced perturbations (Dalziell & McManus, 2004). The speed to recover is measured based on the time required to eliminate the uncertainty-induced perturbation effects (e.g., the time to find a replacement for a human agent, clarify unclear information, or repair a piece of broken equipment). The shorter the recovery time, the greater the adaptive capacity of a project. The capability to recover is measured based on the ability to accelerate the tasks affected by uncertainty-induced perturbations (e.g., the ability to accelerate the tasks by working overtime or inputting more resources) in order to overcome performance losses. The greater the acceleration capability, the greater the adaptive capacity of a project. In the proposed framework, the overall level of project adaptive capacity is determined by both factors.

5.2.5 Assessment of performance deviation

The deviations of key performance indicators (KPIs) are used for measuring systems' capabilities in coping with uncertainty (i.e., resilience) (Dalziell & McManus, 2004). In this research, schedule is selected as a key performance indicator in construction project systems. Accordingly, in the proposed framework, schedule deviation (i.e., total delays in the project schedule) under uncertainty is considered as a measure of project resilience.

The extent of performance deviation in a project depends upon the project vulnerability and adaptive capacity. Without any uncertain events, each project task in the meta-network can be completed within the planned duration since all the required human agents, information and resources for every task are available. If any of these required node entities are interrupted due to uncertainty-induced perturbations, certain tasks will be delayed. The duration of delay in a task depends on: (1) the perturbation effects; and (2) the level of project adaptive capacity. For example, an error in design could cause an information-related perturbation. Then, the project team needs to spend a certain period of time to issue request for information and wait for clarification. However, if the project adaptive capacity is high, the duration of this delay can be reduced. Also, based on the level of project adaptive capacity, the affected tasks may be accelerated after the perturbation effects are eliminated in order to overcome the performance loss. In the proposed framework, tasks in project meta-networks are modeled based on the planned sequence and durations. The total duration of a project is determined based on the aggregation of task durations considering the effects of uncertainty. Accordingly, schedule deviation is calculated based on the difference between the baseline (without consideration of uncertainty) and simulated (under uncertainty) project duration.

5.2.6 Evaluation of planning strategies

Different combinations of planning strategies lead to different levels of project vulnerability and adaptive capacity in projects, and thus, influence project resilience and performance under uncertainty. In the last component of the proposed framework, different planning strategies are evaluated based on their effectiveness in mitigating the negative impacts of uncertainty. Based on their potential influence, there categories of planning strategies were identified in this study: (1) planning strategies that could mitigate project vulnerability by reducing exposure to uncertainty, (2) planning strategies that could mitigate project vulnerability by reducing project complexity, and (3) planning strategies that could enhance project adaptive capacity. Table 5-2 lists examples of planning strategies and their influencing effects on projects.

Table 5-2 Categories and Examples of Planning Strategies

Project emergent properties affected	Ways of influence	Examples
Vulnerability	Reduce exposure to uncertainty	Supplier prequalification; implementation of ICTs; training and teambuilding
	Reduce project complexity	Redundancy in resource
Adaptive Capacity	Enhance project adaptive capacity	Decentralized decision making; subcontractor partnership

As shown in Table 5-2, planning strategies can affect project vulnerability by reducing the level of exposure to uncertain environments or reducing project systems' complexity. Examples of planning strategies that reduce exposure to uncertainty include supplier prequalification, implementation of information and communication technologies (ICTs), and training and teambuilding. These planning strategies could reduce a project system's exposure to resource-related, information-related and human-related uncertain events respectively. For example, adopting a procurement approach based on the prequalification of suppliers can reduce the likelihood of defected materials. Hence, this planning strategy reduces project vulnerability through reducing the likelihood of uncertain events pertaining to resource-related perturbations. Another way to mitigate project vulnerability is to reduce a project's sensitivity to uncertainty-induced perturbations by changing project complexity. When a project is less sensitive to the uncertainty-induced perturbations, the negative impacts can be absorbed or reduced when uncertain events occur. A project's sensitivity to uncertainty-induced perturbations is closely related to the project meta-network's topological structure. It is hypothesized that when a project meta-network has a high level of complexity (measured by network density in this study), its sensitivity to uncertainty-induced perturbations could be high as well. It is because a high level of density implies that there is a high level of interdependencies among human agent, resource, information, and task nodes in a project meta-network. Thus, a perturbation in any single node may have ripple effects. One example of planning strategies related to vulnerability mitigation by reducing project complexity is resource redundancy. If redundancy in resources is adopted as a planning strategy in a project, additional resource nodes are added in the project meta-network as backup resources. Accordingly, if one resource node is disrupted, the task can still be implemented with the backup resource node. Hence, the vulnerability of the project is reduced. This hypothesis is tested later in the simulation experiments of the case study. Planning strategies also can affect a project's adaptive capacity. Two examples of planning strategies related to adaptive capacity are considered in this study: decentralized decision making and subcontractor partnership. Decentralized decision-making helps to better deal with the impacts of uncertain events and take actions faster after uncertain events occur (Dalziell & McManus, 2004). Developing partnership with subcontractors is another example to increase project adaptive capacity. Subcontractors that have long-term partnership with general contractors are usually more flexible in reaction and willing to work overtime and contribute more resources to accelerate their work in order to adapt to the unexpected situations. Thus, both planning strategies can increase a project's speed and capacity to recover from uncertainty-induced perturbations.

5.3 Case Study

The proposed dynamic meta-network modeling framework was applied in 3 case studies from 2 complex commercial construction projects in South Florida. Each case study unit is a project system related to one part of the whole project with independent work packages. Case study 1 is related to the elevator system design and construction of a commercial project. Case study 2 is related to the wall system design and construction in the same commercial project. Case study 3 is related to the pile cap design and construction in the foundation system of another commercial project. The three case study units were selected based on their high levels of complexity. Each case study unit has various stakeholders involved and many different resources and information required.

5.3.1 Date collection

Different sets of data collected for case studies are listed in Table 5-3. To obtain all the data required, different methods were used in data collection, including semi-structured interview with the key project personnel (e.g., project manager, project engineer); document review upon permission (e.g., schedule, daily logs, and monthly progress reports) and direct observations in jobsite (e.g., attending project weekly meetings).

Table 5-3 Case Study Data Collected

Purpose	Capturing the basic features of projects	Capturing uncertainty in projects	Capturing project behaviors under uncertainty
Data	• Human agent, resource, information and task nodes • Interrelationships between nodes identified • Sequence and duration of tasks	• Uncertainties in projects • Direct impacts of the uncertainties • The likelihood of different uncertainties	• Project recovery speed and capability when uncertainty events occur • The planned and actual schedule performance outcomes

During the period between June 2015 and April 2016, weekly visits to the project job sites were made to collect data for development of project meta-network models and implementation of dynamic network analysis. The data collected from each case study are presented as follows.

(1) Case study 1

In this case study, the design and construction processes related to an elevator system (Figure 5-2) in a commercial project were modeled. Construction of the elevator system requires close collaboration between different trades such as concrete sub, steel sub, elevator sub, and curtain wall sub. In this specific project, the variations in the actual locations of steel embeds had been identified to exceed the tolerance. Thus, a redesign process was required. Table 5-4 summarizes the basic information collected for case study 1, including the human agents, information, resources, and tasks, their interdependencies, and task durations. The information was used for developing the computational model.

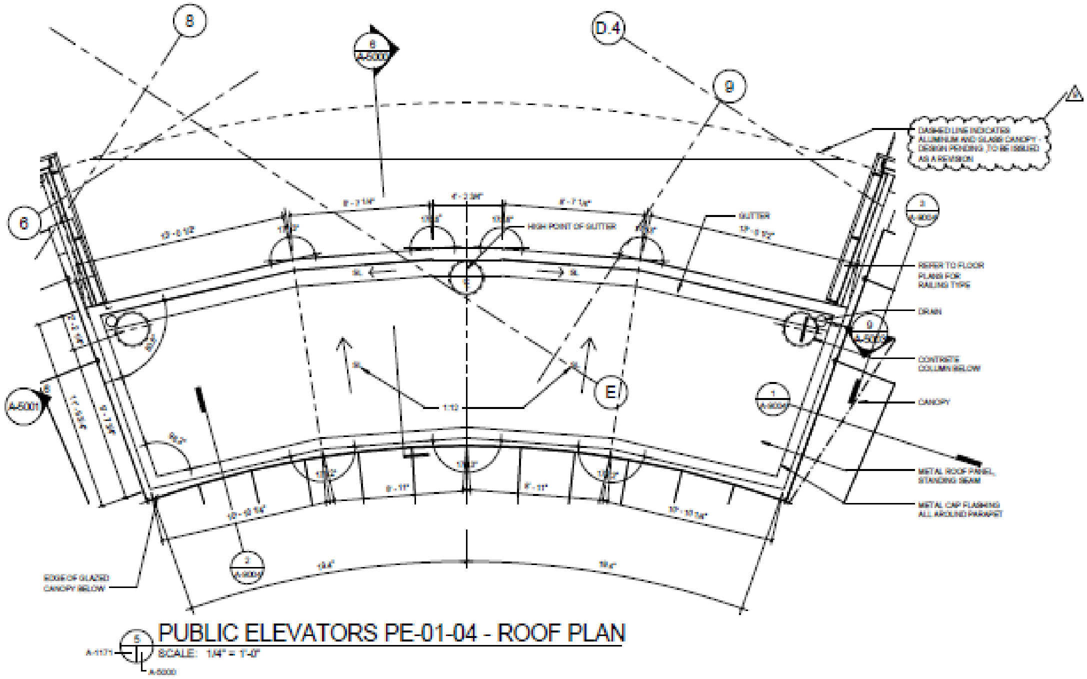


Figure 5-2 Roof Plan of the Elevator System of Case Study 1

Data related to the uncertain environment of case study 1 were collected from interviews with multiple project personnel. As shown in Table 5-5, the project system studied has a low level (5%) of high-disturbance human-related uncertainty, a medium level (10%) of medium-disturbance human-related uncertainty, and a medium level (10%) of low-disturbance human-related uncertainty. Accordingly, the overall human-related uncertainty level can be calculated as: $1-(1-5\%)(1-10\%)(1-10\%)=23.05\%$. Similarly, the overall information-related uncertainty level is 35.20%, and overall resource-related uncertainty level is 31.60%.

Table 5-4 Basic Information for Case Study 1

Task ID	Tasks	Precedence	Duration (days)	Human agents	Resources	Information
1	Install steel embeds	-	14	Concrete Sub	Steel embeds	Architecture drawings
2		1				Specifications
3	Pour concrete	2	14	Concrete Sub	Concrete	Architecture drawings
					Concrete pump	Specifications
4	Survey	3	2	Steel Sub	Survey instruments	Architecture drawings
				CM		Specifications
				Surveyor		
5	Redesign	4	21	Steel Sub		Actual locations of embeds
				CM		Architecture drawings
				Designer		Specifications
				Owner		
				Curtain Wall Sub		
				Elevator Sub		
6	Install structural steel	5	14	Steel Sub	Steel	Architecture drawings
					Cranes	Specifications
					Scaffolds	Revised design
						owner's approval
7	Install elevator support steel	6	10	Elevator Sub	Elevator support steel	Architecture drawings

Task ID	Tasks	Precedence	Duration (days)	Human agents	Resources	Information
					Cranes	Specifications
					Scaffolds	Revised design
						Owner's approval
8	Build machine room	7	21	Elevator Sub	Elevator drives	Architecture drawings
						Specifications
						Revised design
						Owner's approval
9	Install elevator cabs	8	21	Elevator Sub	Elevator cabs	Architecture drawings
						Specifications
						Revised design
						Owner's approval
10	Install MEP rough-in	9	14	Electrical Sub	Electrical systems	Architecture drawings
				Mechanical Sub	Mechanical systems	Specifications
				Fire Protection Sub	Fire protection systems	Revised design
						City regulations
						owner's approval
11	Install curtain wall	10	21	Curtain Wall Sub	Support framing	Architecture drawings
					Curtain wall	Specifications
					Cranes	Revised design
					Scaffolds	owner's approval
12	Final inspection	11	2	Inspector		Architecture drawings

Task ID	Tasks	Precedence	Duration (days)	Human agents	Resources	Information
				CM		Specifications
				Owner		Revised design
						City regulations

Table 5-5 Likelihood of Uncertainties in Case Study 1

Likelihood of Uncertainties (Low: 5%; Medium: 10%; High: 20%)		
Human-related	High-disturbance	Low
	Medium-disturbance	Medium
	Low-disturbance	Medium
Information-related	High-disturbance	Medium
	Medium-disturbance	Medium
	Low-disturbance	High
Resource-related	High-disturbance	Low
	Medium-disturbance	Medium
	Low-disturbance	High

Another set of important data captured is related to project adaptive capacity in terms of project recovery speed and capability. During the interview with project personnel, the recovery speed for each type and level of uncertain events in this specific project was captured. In addition, possible improvements in project adaptive capacity were asked. As shown in Table 5-6, three levels of adaptive capacity and corresponding recovery speed were captured. For example, L1 is the project current adaptive capacity level. At this level, it takes 21 days, 14 days, or 3 days to recover from a high-disturbance, medium-disturbance or low-disturbance human-related uncertain event, respectively. If the adaptive capacity increases in this project by adopting additional planning strategies, the recovery speed will increase accordingly. For example, if the adaptive capacity of this project increases to L2, the recovery time for a high-disturbance, medium-disturbance or low-disturbance human-related uncertain event can be reduced to 14 days, 10 days, or 2 days, respectively. If the adaptive capacity continues to increase to L3, the corresponding recovery time can be reduced to 10 days, 5 days, or 1 day, respectively. As shown in Table 5-6, different levels of adaptive capacity also lead to different recovery speed related to information-related and resource-related uncertain events. Besides, different levels of project adaptive capacity also lead to different levels of recovery capabilities. In this case project, when adaptive capacity is at L2, the project will have the capability to accelerate the affected tasks at a rate of 110% after uncertainty-induced perturbations occur. When adaptive capacity increases to L3, the project will have the capability to accelerate the affected tasks at a rate of 120% after uncertainty-induced perturbations occur.

Table 5-6 Recovery Speed from Different Uncertain Events in Case Study 1

Recovery speed (days)				
Uncertainties		Adaptive Capacity		
		L1	L2	L3
Human-related	High-disturbance	21	14	10
	Medium-disturbance	14	10	5
	Low-disturbance	3	2	1
Information-related	High-disturbance	28	21	14
	Medium-disturbance	14	10	7
	Low-disturbance	7	4	2
Resource-related	High-disturbance	21	14	7
	Medium-disturbance	14	10	7
	Low-disturbance	12	8	5

(2) Case study 2

Case study 2 is related to the design and construction of the south wall system in the same commercial project as case study 1. Construction of the wall system includes various components such as interior wall, exterior wall, concrete ramp, and MEP systems (Figure 5-3). The interactions between different trades in a limited working space have led to a high level of complexity and uncertainty in this case study unit.

Table 5-7 summarizes the basic information collected for case study 2, including the human agents, information, resources, and tasks, their interdependencies, and task durations, which were used for developing the computational model. Since case study 2 is from the same project as case study 1, the uncertain environment and some project behaviors under uncertainty are the same in the two case study units. Thus, the uncertain environment and the recovery speed of case study 2 can refer to Table 5-5 and Table 5-6.

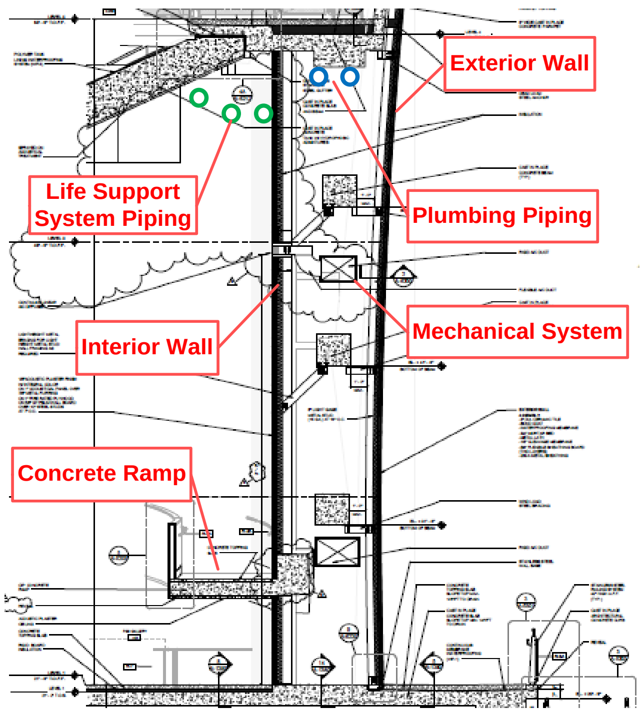


Figure 5-3 Plan of the South Wall System of Case Study 2

Table 5-7 Basic Information for Case Study 2

Task ID	Tasks	Precedence	Durations (days)	Human agent	Information	Resource
1	Architecture design	-	20	architect designer	owner's requirement	
2	Structure design	1	15	structure engineer	owner's requirement	
					architecture design	
3	Life support system design	1	10	life support system designer	owner's requirement	
					architecture design	
4	MEP design	1	10	MEP designer	owner's requirement	
					architecture design	
5	Shop drawing review	2,3,4	2	architect designer	architecture design	
				structure engineer	structure design	
				life support system designer	life support system design	
				MEP designer	MEP design	
				owner's representative		
				CM		
				executive architect		
6	Decide work sequence	5	5	CM	architecture design	
					structure design	
					life support system design	
					MEP design	
					project schedule	
					wall sub requirement	
					concrete sub requirement	

Task ID	Tasks	Precedence	Durations (days)	Human agent	Information	Resource
					mechanical sub requirement	
					plumbing sub requirement	
7	Select wall material	6	2	owner	work sequence	
				owner's representative	cost of wall alternatives	
				CM		
				executive architect		
				wall sub		
8	Build ramp	7	15	concrete sub	architecture design	concrete
					structure design	reinforcement
					project schedule	concrete pump
					work sequence	boom lifts
9	Install exterior wall	8	10	wall sub	architecture design	scaffold
					structure design	drywall
					life support system design	densglass board
					MEP design	STC rated plaster
					project schedule	
					work sequence	
10	Mechanical system installation	9	5	mechanical sub	architecture design	AC
					structure design	boom lifts
					MEP design	
					project schedule	

Task ID	Tasks	Precedence	Durations (days)	Human agent	Information	Resource
					work sequence	
11	Plumbing system installation	9	8	plumbing sub	architecture design	HDPE
					structure design	electro-fusion device
					life support system design	boom lifts
					project schedule	
					work sequence	
12	Life support system installation	9	12	plumbing sub	architecture design	plumbing piping
					structure design	boom lifts
					MEP design	
					project schedule	
					work sequence	
13	Install interior wall	10,11,12	10	wall sub	architecture design	scaffold
					structure design	densglass board
					project schedule	
					work sequence	

(3) Case study 3

Case study 3 is related to the foundation system, specifically pile caps, in another commercial construction project (Figure 5-4). Table 5-8 summarizes the basic information used for developing the computational model. Similarly, as the previous two cases, the uncertain environment of case study 3 was captured (Table 5-9) as well as the project recovery speed at different levels of adaptive capacity (Table 5-10). In terms of recovery capability, when adaptive capacity is at L2, the project will have the capability to accelerate the affected tasks at a rate of 110% after uncertainty-induced perturbations occur. When adaptive capacity increases to L3, the project will have the capability to accelerate the affected tasks at a rate of 120% after uncertainty-induced perturbations occur.

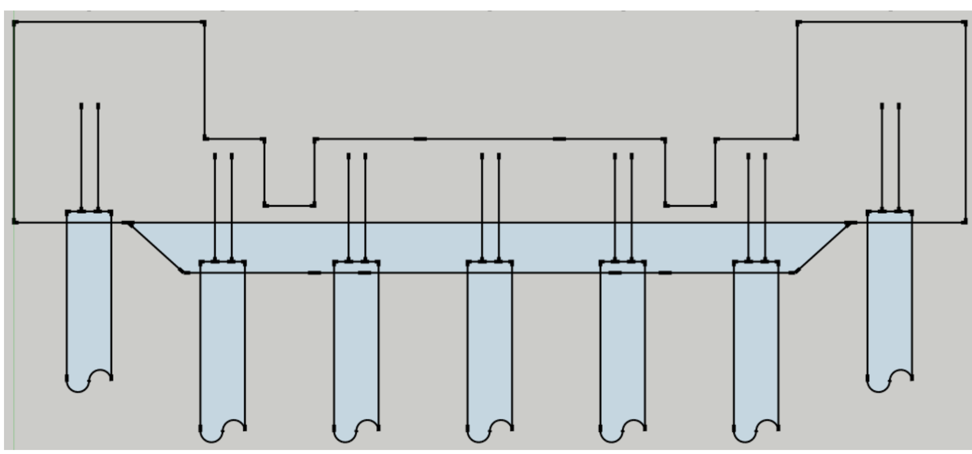


Figure 5-4 Plan of the Foundation System of Case Study 3

Table 5-8 Basic Information for Case Study 3

Task ID	Task	Precedence	Duration (days)	Human Agent	Resource	Information
1	survey	-	1	sub A	total station	drawings
2	excavation	1	3	sub A	excavator	logistic plans
					loader	drawings
3	layout	2	1	surveyor	total station	pile projections
4	pile chipping	3	4	sub B	pile chipper	surveyor marks
5	as-built survey	4	1	surveyor	total station	
6	form pile cap	5	2	sub C	forms	pile cap dimensions
					form accessories	as-built information
						concrete specification
7	waterproofing installation	6	2	sub D	waterproofing	waterproofing specifications
8	waterproofing inspection	7	1	waterproofing inspector		waterproofing specifications
				GC		
9	reinforcement installation	8	4	sub C	reinforcement	drawings
					reinforcing accessories	reinforcement specifications
						as-built information
10	inspect form and reinforcing	9	1	private inspector A		drawings
				GC		reinforcement specifications
						as-built information

Task ID	Task	Precedence	Duration (days)	Human Agent	Resource	Information
						concrete specification
11	pour concrete	10	1	sub C	concrete	drawings
					concrete pump	concrete specifications
					concrete truck	as-built information
					trowels	
12	test concrete	10	1	private inspector B	test instruments	concrete specifications
				GC		
13	strip forms	11,12	2	sub C	hand tools	concrete specifications
14	2nd waterproofing inspection	13	1	waterproofing inspector		waterproofing specifications
				GC		
15	backfill	14	2	sub A	trucks	compaction specifications
					clean soil	
					tamper	

Table 5-9 Likelihood of Uncertainties in Case Study 3

Likelihood of Uncertainties (Low: 5%; Medium: 10%; High: 20%)		
Human-related	High-disturbance	Low
	Medium-disturbance	High
	Low-disturbance	High
Information-related	High-disturbance	Medium
	Medium-disturbance	High
	Low-disturbance	High
Resource-related	High-disturbance	Medium
	Medium-disturbance	High
	Low-disturbance	High

Table 5-10 Recovery Speed from Different Uncertain Events of Project in Case Study 3

Recovery speed (days)				
Uncertainties		Adaptive Capacity		
		L1	L2	L3
Human-related	High-disturbance	20	10	5
	Medium-disturbance	10	5	2
	Low-disturbance	5	2	1
Information-related	High-disturbance	20	10	5
	Medium-disturbance	5	2	1
	Low-disturbance	2	1	0.5
Resource-related	High-disturbance	20	10	5
	Medium-disturbance	10	3	1
	Low-disturbance	2	1	0.5

5.3.2 Computational model

The computational models for each case study were developed in two steps. In the first step, project meta-networks were developed using ORA NetScenes based on the data collected. Figure 5-5, Figure 5-6, and Figure 5-7 show the project meta-network for case study 1, 2, and 3, respectively. In the second step, based on the meta-network models and other related information collected, computational models for vulnerability assessment and schedule deviation assessment under uncertainty were developed for each case study unit in MATLAB. Those computational models were used for conducting Monte-Carlo simulation experiments in this research. Sample codes for base scenario in each case study unit can be found in Appendix at the end of this dissertation.

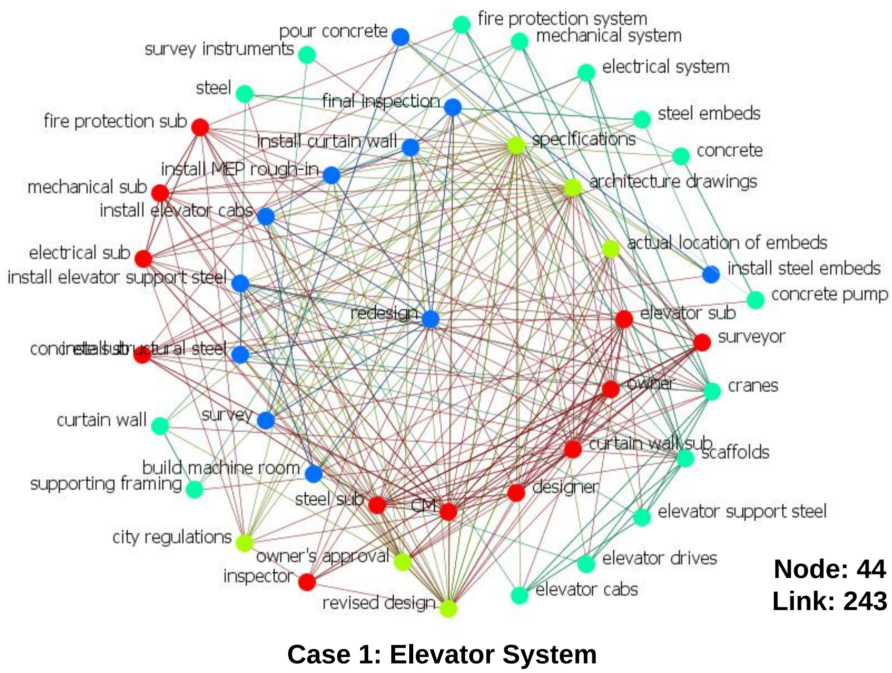
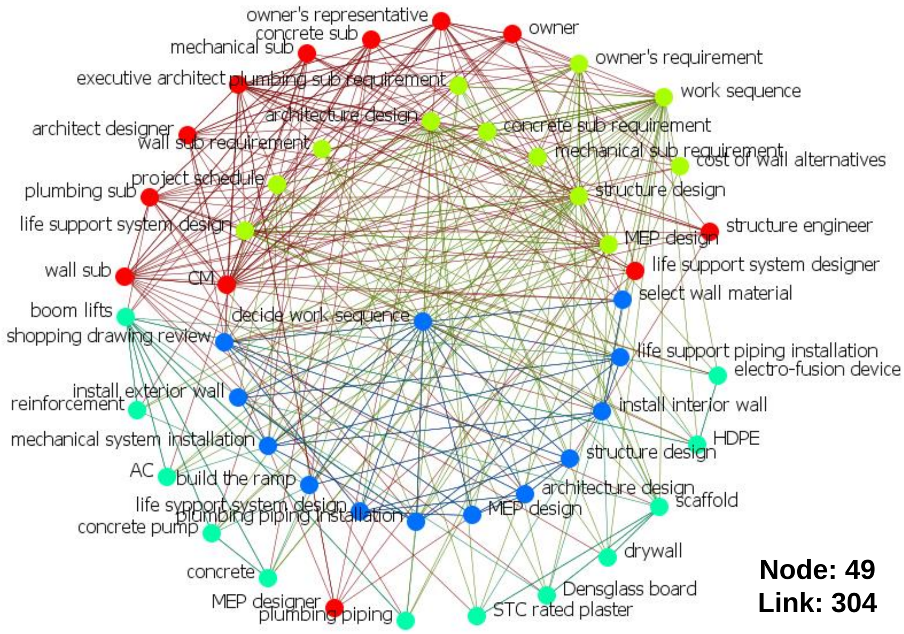
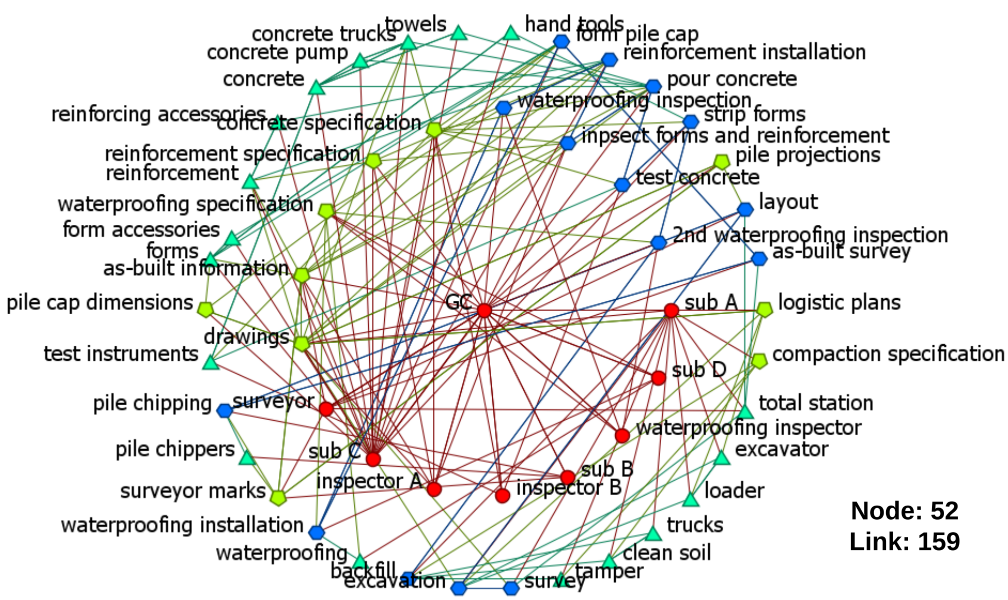


Figure 5-5 Project Meta-network for Case Study 1



Case 2: South Wall System

Figure 5-6 Project Meta-network for Case Study 2



C3: Foundation System

Figure 5-7 Project Meta-network for Case Study 3

Before the computational models were used for simulation experiments, verification and validation of the computational models were conducted in order to ensure that the computational models accurately embodies the theoretical logic, and the simulation results can be interpreted with confidence (Davis et al., 2007). Computational model verification includes the processes and techniques that the model developer uses to assure that his or her model is correct and matches any agree-upon specifications and assumptions, while validation refers to the processes and techniques that the developer, customer and decision makers jointly use to assure that the results and conclusions represent and are applicable in the real world to a sufficient level of accuracy (Carson, 2002). There are many techniques for simulation model verification and validation (Sargent, 2011). In this research, several techniques were selected for the purpose of model verification and validation including internal validation, extreme condition tests, predictive validation as well as face validation (Figure 5-8). After the simulation models were developed for each case, the selected verification and validation techniques were used to assure the correctness and accuracy of the simulation models. For example, when doing predictive validation, the predictive schedule deviation obtained from simulation and the actual delay in the case study projects were compared. In case study 2, the simulation result of project schedule deviation under the current uncertain environment is 161 days on average, while the actual delay due to this component in the project is around 6 months (i.e., 180 days) according to the time impact analysis. The comparison shows that the simulation result and actual project performance are close, and thus, the simulation model reflects the real world to a sufficient level of accuracy. In face validation, subject matter experts, including project personnel in the two projects, were interviewed to validate the completeness and accuracy of the models as well as the reasonability of the simulation results. Based on the comments from the subject matter experts, the models were then modified until the completeness and accuracy were confirmed by them.

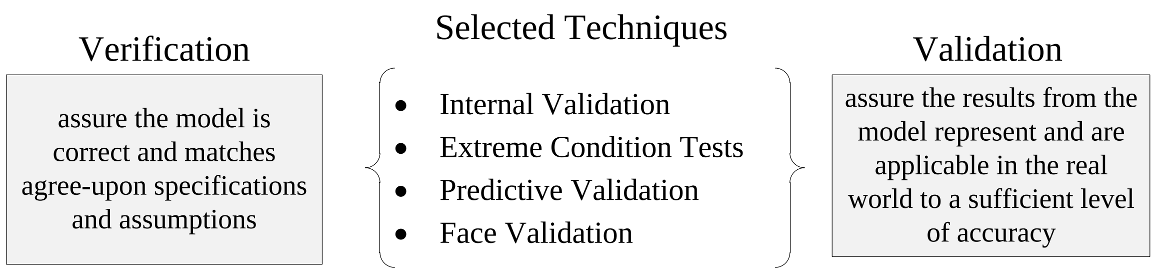


Figure 5-8 Verification and Validation Techniques

5.3.3 Simulation experiment

Different sets of simulation experiments were conducted in order to explore theoretical constructs related to the research objectives. First set of simulation experiments is to investigate project vulnerability based on exposure to uncertainty and complexity. Simulation experiments with varying levels of exposure to uncertainty and complexity were conducted in each case and results were compared across cases. In the second set of simulation experiments, different simulation scenarios were created based on combinations of planning strategies in each case. Each simulation scenario has a specific level of project vulnerability and adaptive capacity. Monte-Carlo simulation experiments were conducted in each of the simulation scenarios. Thus, the simulation results can be used to investigate the relationships between project vulnerability, adaptive capacity and project schedule deviation. In addition, the simulation results from the second set of simulation experiments can be used to evaluate the effectiveness of different planning strategies in enhancing project resilience. In section 5.4, three sets of findings from the simulation experiments are explained in details.

5.4 Results and Findings

The simulation results and findings are presented as three sets of theoretical constructs.

5.4.1 Project exposure to uncertainty, complexity and vulnerability

Theoretical constructs related to project exposure to uncertainty, complexity, and vulnerability identified in the simulation experiments across three cases are as follows:

Theoretical construct 1a: Project vulnerability is positively correlated with exposure to uncertainty.

Theoretical construct 1b: Project vulnerability is positively correlated with project complexity.

During the simulation experiments, project vulnerability was assessed based on the decrease in a project's meta-network efficiency due to uncertainty-induced perturbations. Figure 5-9, Figure 5-10, and Figure 5-11 show the simulation results of project vulnerability from 1000 runs of Monte-Carlo simulation in the base scenario of case 1, 2 and 3. In each of these figures, a bell curve that best fits the simulation results was plotted. Table 5-11 summarizes the vulnerability simulation results in the three cases. The value of project vulnerability represents the percentage of tasks that cannot be successfully implemented due to uncertainty. For example, the mean value of project vulnerability in case 1 is 0.60. This result means that on average, 60% of tasks in this case could not be conducted successfully as planned with the existing uncertain environment and the base-case planning strategies.

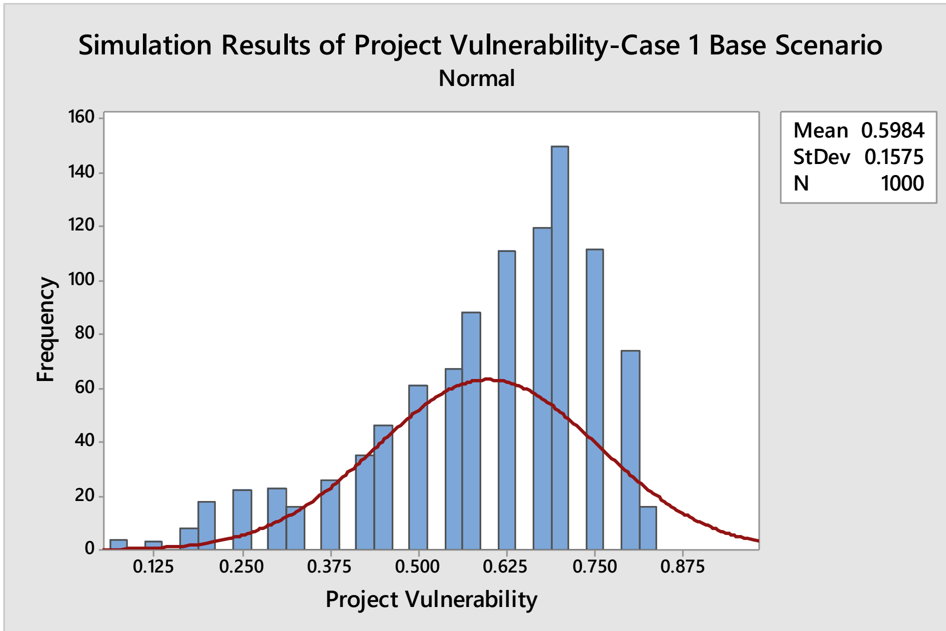


Figure 5-9 Project Vulnerability of Case Study 1 in Base Scenario

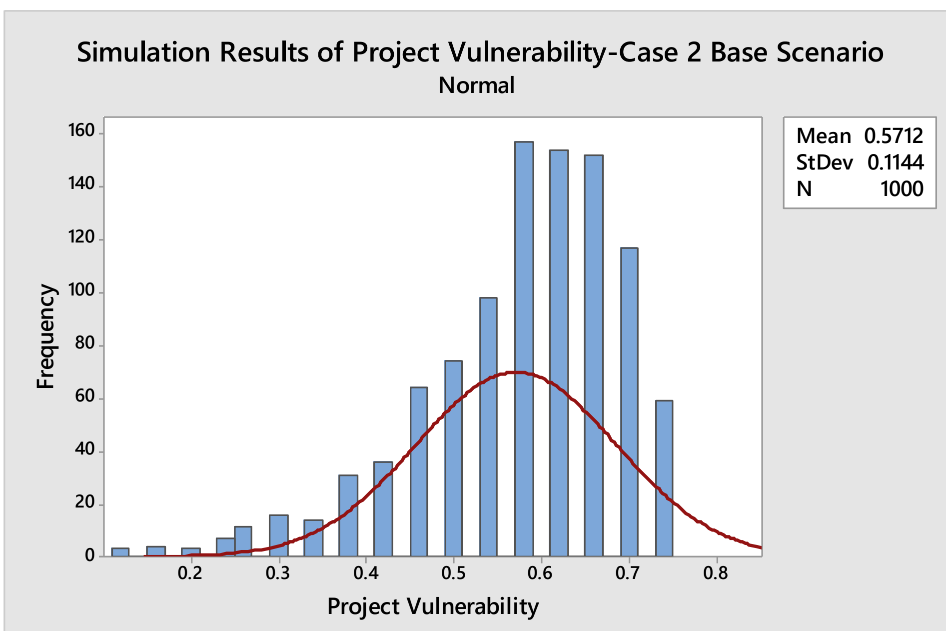


Figure 5-10 Project Vulnerability of Case Study 2 in Base Scenario

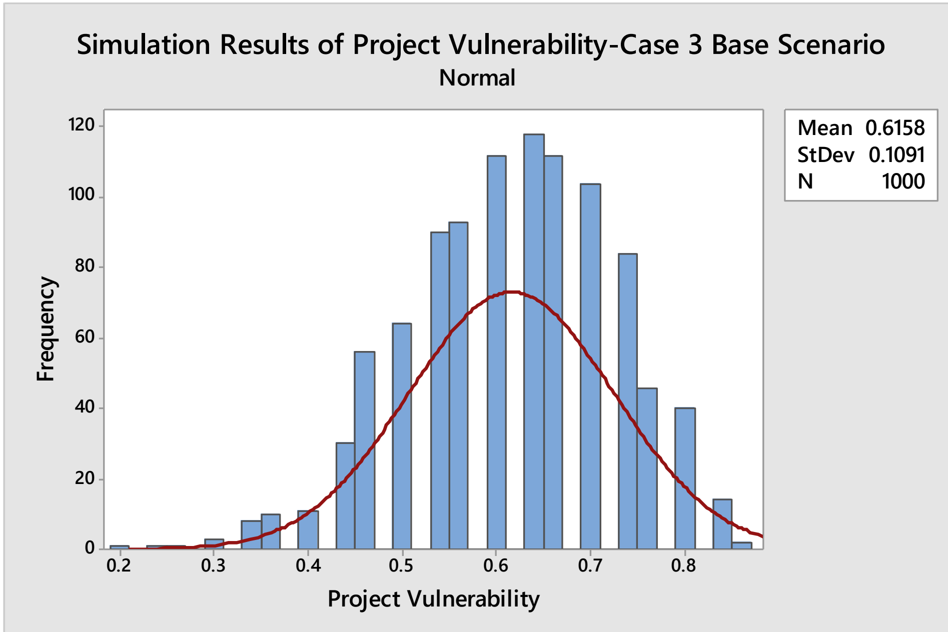


Figure 5-11 Project Vulnerability of Case Study 3 in Base Scenario

Table 5-11 Project Vulnerability of Case 1, 2, and 3 in Base Scenarios

Case	Project Vulnerability	
	Mean	SD
Case1	0.60	0.16
Case2	0.57	0.11
Case3	0.62	0.11

In order to explore the influencing factors of project vulnerability, the first experiment is to change the level of exposure to uncertainty in each case, and then compare the changes in project vulnerability within cases. Table 5-12 shows simulation scenarios VT1 (less exposure to uncertainty) and VT2 (more exposure to uncertainty) for case study 1 and 2. In scenario VT1, the level of exposure to uncertainty for each type of uncertainty at each category was decreased by one level (e.g., from high to medium, or from medium to low). In scenario VT2, the level of exposure to uncertainty for each type of uncertainty at each category was increased by one level (e.g., from low to medium, or from medium to high). The overall human-related, information-related and resource-related uncertainties in VT1 and VT2 were then calculated using equations 5.1-5.3. Similarly, scenario VT1 and VT2 were generated for case study 3.

Table 5-12 Simulation Scenarios by Changing Exposure to Uncertainty in Case 1 and 2

Uncertainty Sources	Base Scenario	Scenario VT1 (less exposure)	Scenario VT2 (more exposure)
Human-related	0.2305	0.0975	0.424
Information-related	0.352	0.18775	0.488
Resource-related	0.316	0.145	0.424

Project vulnerability in the comparative scenarios with varying levels of exposure to uncertainty was then assessed in each case. As shown in Figure 5-12, Figure 5-13, and Figure 5-14, in all three cases, a lower level of exposure to uncertainty significantly reduces project vulnerability. On the contrary, project vulnerability increases with a higher level of exposure to uncertainty. In case 3, the increase in project vulnerability is not significant when the exposure to uncertainty is increased since the original exposure to uncertainty in base scenario is already high.

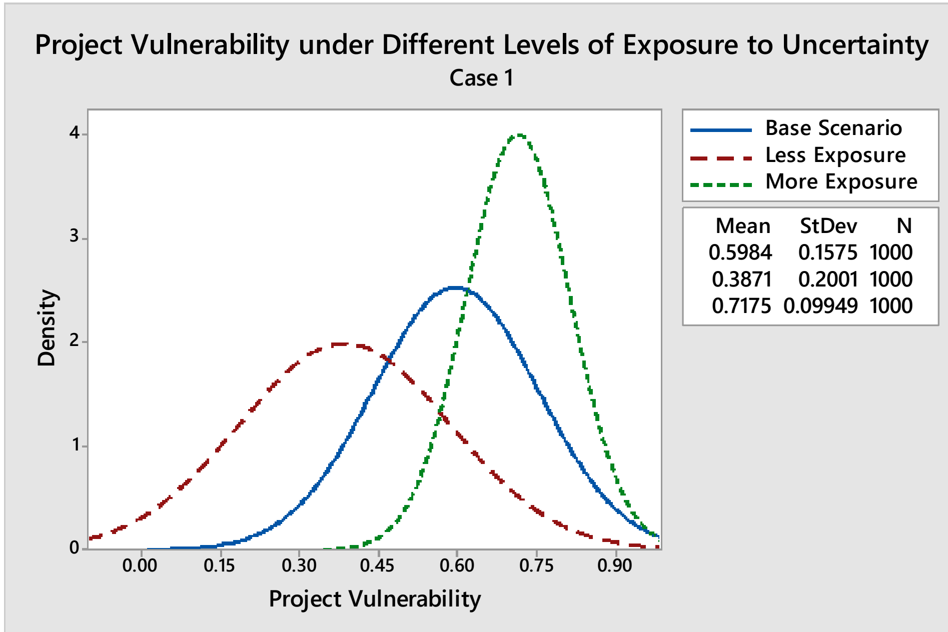


Figure 5-12 Project Vulnerability under Different Levels of Exposure to Uncertainty in Case 1

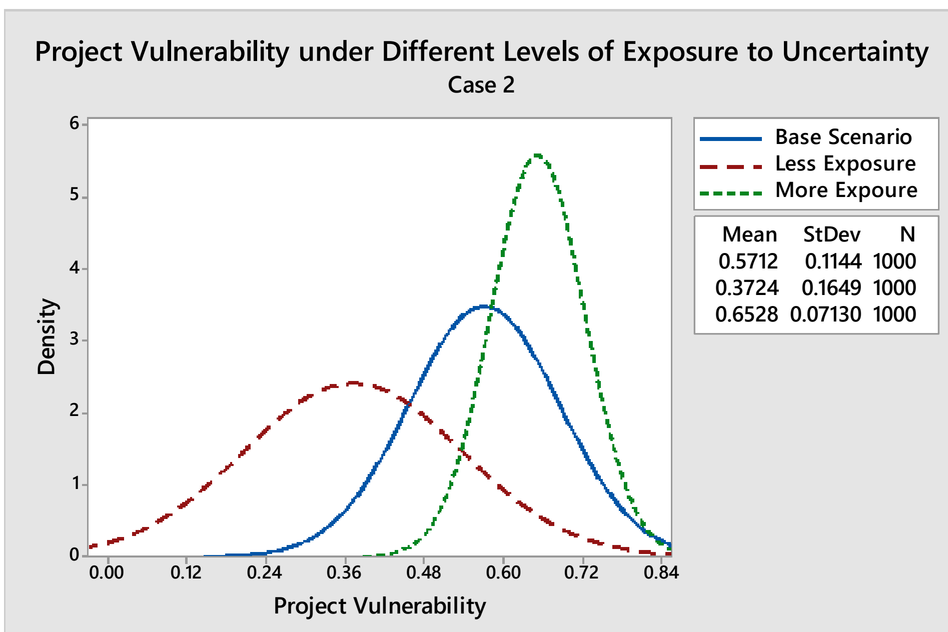


Figure 5-13 Project Vulnerability under Different Levels of Exposure to Uncertainty in Case 2

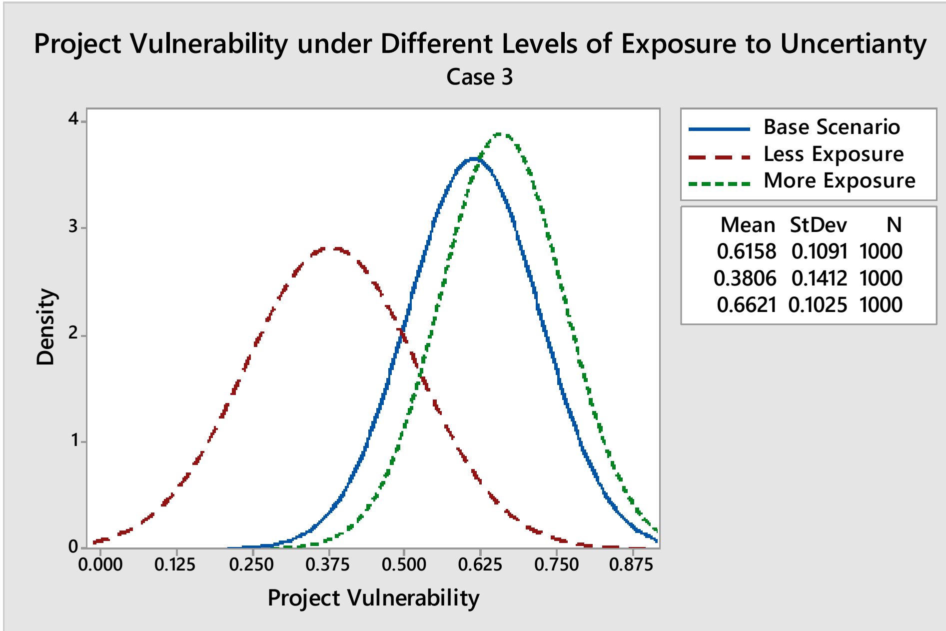


Figure 5-14 Project Vulnerability under Different Levels of Exposure to Uncertainty in Case 3

Project vulnerability is not only affected by the level of exposure to uncertainty, but also by project complexity. In this study, project complexity is measured by meta-network density. Meta-network density is calculated as the sum of the links divided by the sum of the possible links across all individual networks in a meta-network. The value of the meta-network density varies from 0 to 1. The higher the value, the more complex a project meta-network. However, it doesn't mean that the minimum possible value and maximum possible value of the complexity of a project meta-network are 0 and 1. The level of complexity is determined by the nature of a project, such as task assignment.

To investigate the influence of meta-network complexity on project vulnerability, a simulation experiment was first conducted in case 2. Based on the nature of case 2, two planning strategies which affect complexity were considered: division of labor and redundancy in resources. When division of labor is adopted as a planning strategy, one human agent node is only assigned to one task. Thus, additional human agent nodes need to be added and some of the tasks originally assigned to the same human agent are assigned to the human agents added. When redundancy in resource is adopted as a planning strategy, additional resource nodes are added and linked to the corresponding human agent, information, resource, and task nodes. Figure 5-15 shows the project meta-networks of case 2 when adopting these two planning strategies, respectively. The project complexity was changed from 0.259 in base scenario into 0.247 and 0.243 in the two comparative scenarios. Monte-Carlo simulation experiments were then conducted in the two scenarios. Figure 5-16 shows the distributions of project vulnerability in base scenario as well as the two comparative scenarios of case 2. It shows that the value of project vulnerability is lower when the project complexity is at lower levels in case 2 under the same exposure to uncertainty.

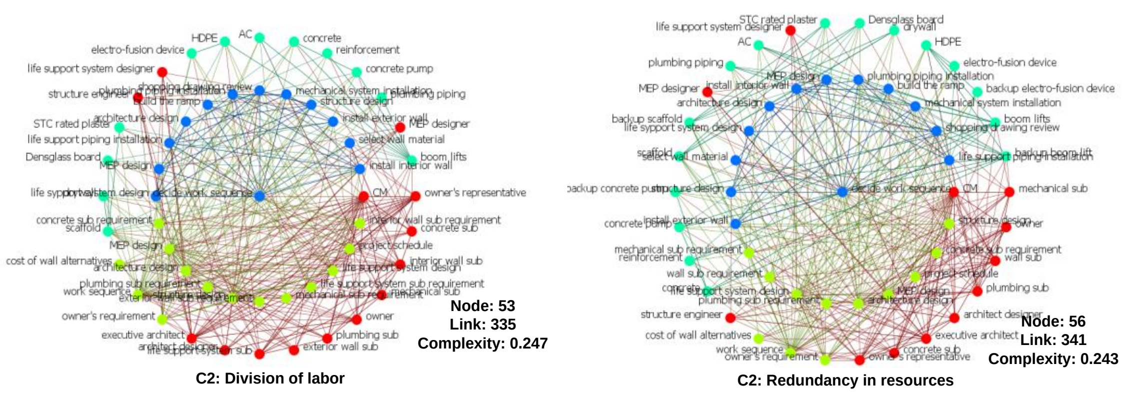


Figure 5-15 Project Meta-networks in Simulation Scenarios of Case 2

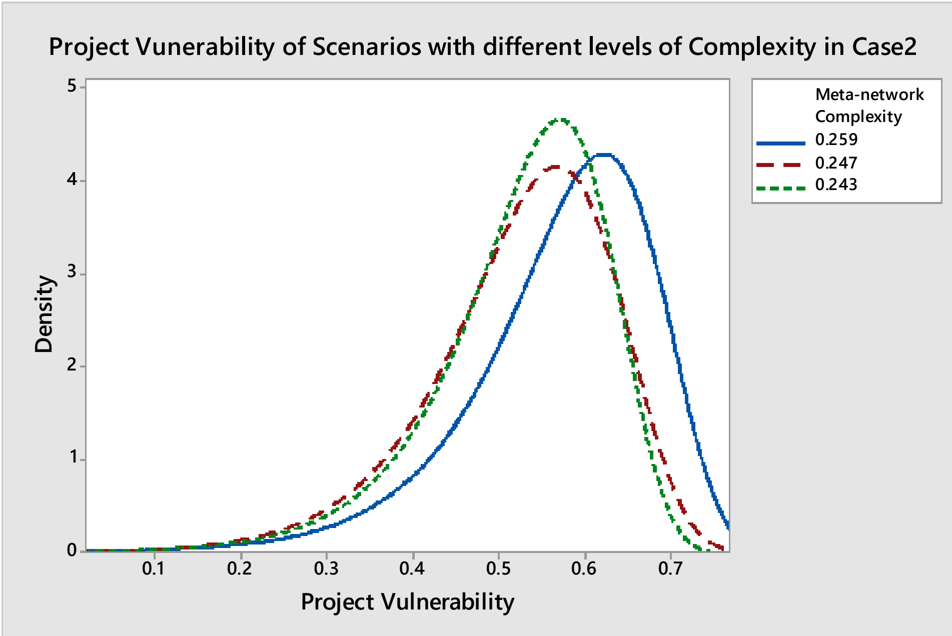


Figure 5-16 Project Vulnerability across Different Simulation Scenarios in Case 2

Another simulation experiment was done in order to compare project vulnerability across different cases. When comparing project vulnerability in case 1, 2, and 3, it is observed that they have similar levels of project vulnerability, although in case 3, the exposure to uncertainty is much higher compared to case 1 and 2. One possible reason might be the varying levels of complexity in these cases. While the values of project complexity in case 1 and 2 are 0.257 and 0.259 respectively, the value of project complexity in case 3 is only 0.120. In order to further test the impact of project complexity on vulnerability, a simulation scenario case3-VT3 was developed. In case3-VT3, the level of exposure to uncertainty in case 3 was changed into the same level as case 1 and 2. Monte-Carlo simulations were then conducted in case3-VT3. Figure 5-17 shows simulation results of project vulnerability in base scenarios of case 1, 2 and 3, as well as case3-VT3. When comparing project vulnerability in the base scenarios of case 1 and 2 (i.e., case1-BS and case 2-BS) and case3-VT3, it is shown that under the same level of exposure to uncertainty, a project with a smaller value of complexity is less vulnerable compared to projects with higher values of complexity (Table 5-13).

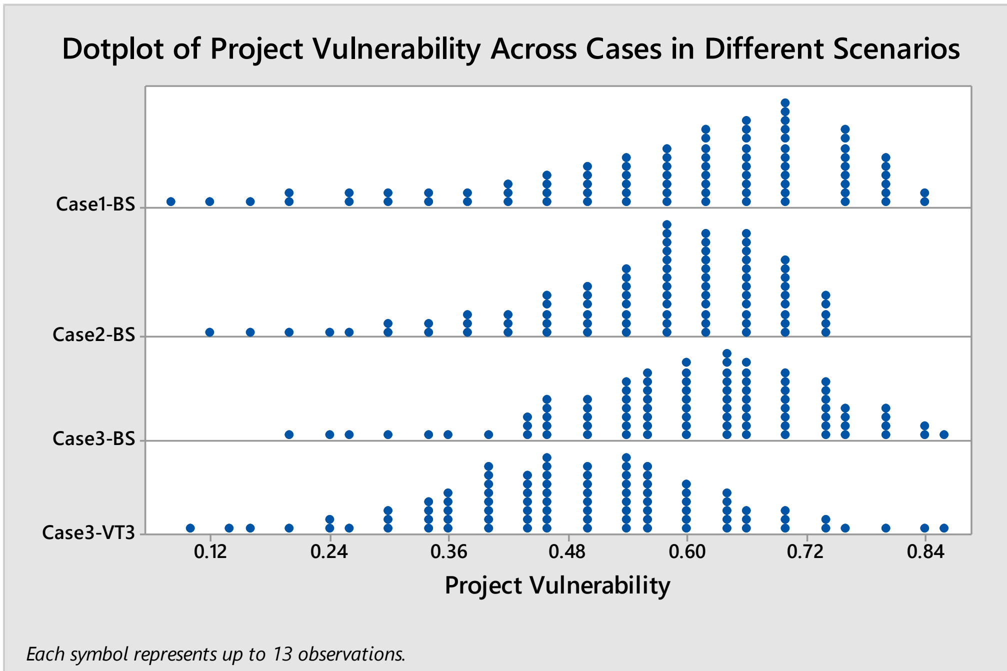


Figure 5-17 Project Vulnerability across Cases in Different Simulation Scenarios

Table 5-13 Comparison of Project Vulnerability in Different Scenarios

Cases and Scenarios	**Exposure to Uncertainty**	**Project Complexity**	**Project Vulnerability**	
			Mean	SD
Case1-BS	L1	0.257	0.60	0.16
Case2-BS	L1	0.259	0.57	0.11
Case3-BS	L2 (L2>L1)	0.120	0.62	0.11
Case3-VT3	L1	0.120	0.49	0.12

The findings related to project vulnerability, exposure to uncertainty, and project complexity help project managers and decision makers to: (1) assess the level of project vulnerability predictively; and (2) consider possible ways to mitigate project vulnerability proactively. Before a project starts, project managers and decision makers can assess the level of project vulnerability based on current exposure to uncertainty and project topological structure. If the level of project vulnerability exceeds the acceptable level, project managers and decision makers should consider taking measures in order to mitigate project vulnerability proactively either by reducing exposure to uncertainty or by reducing project complexity. Planning strategies which have the potential effects for reducing exposure to uncertainty or project complexity are discussed later in the third set of theoretical constructs.

5.4.2 Project vulnerability, adaptive capacity, and schedule deviation

Theoretical constructs related to project vulnerability, adaptive capacity and schedule deviation identified in the simulation experiments across three cases are as follows:

Theoretical construct 2a: There is a positive correlation between project vulnerability and schedule deviation under uncertainty. The correlation is sensitive to the level of adaptive capacity.

Theoretical construct 2b: There is a negative correlation between project adaptive capacity and schedule deviation under uncertainty. The correlation is sensitive to the level of project vulnerability.

The findings above were obtained through analyzing simulation results of project schedule deviations under uncertainty in different simulation scenarios as shown in Table 5-14. In Table 5-14, some of the planning strategies have the effects of reducing project vulnerability (i.e., redundancy in resource, supplier qualification, implementation of ICTs, and training and teambuilding). Other planning strategies are able to enhance project adaptive capacity (i.e., decentralized decision-making and partnership). Decentralized decision-making is assumed to be able to increase the level of project adaptive capacity from L1 to L2 based on interviews with project personnel. Also, based on interviews with project personnel, if both decentralized decision-making and subcontractor partnership are adopted, the level of project adaptive capacity will continue to increase into L3. In total, 47 simulation scenarios were generated. Each scenario is a combination of different planning strategies. For each of the three case studies, Monte-Carlo simulations were conducted to capture project schedule deviation from planned duration in each of the simulation scenarios with varying levels of project vulnerability and adaptive capacity.

Figure 5-18 shows the simulation results of different scenarios in case 1 in a combination of four graphs. In the first three graphs, each figure shows the relationship between project vulnerability and schedule deviation under project adaptive capacity L1, L2 and L3 respectively. In the last graph, the first three graphs are overlaid on the same graph in order to better capture and compare the impacts of different levels of project vulnerability and adaptive capacity on schedule deviation. For example, in the first graph of Figure 5-18, each data point represents the level project vulnerability and schedule deviation under uncertainty in one simulation scenario. The value of project vulnerability is the mean value obtained from 1000 runs of Monte-Carlo simulation of vulnerability assessment. The value of schedule deviation is the mean value from 1000 runs of Monte-Carlo simulation of schedule deviation assessment. In all the simulation scenarios in the first graph, the level of project adaptive capacity is at L1. Similarly, in the second and third graphs of Figure 5-18, the results of project vulnerability and schedule deviation simulation under adaptive capacity L2 and L3 are shown respectively.

Table 5-14 Planning Scenarios Considered in this Study

	S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20	S21	S22	S23	S24	S25	S26	S27	S28	S29	S30	S31	S32	S33	S34	S35	S36	S37	S38	S39	S40	S41	S42	S43	S44	S45	S46	S47
Redundancy in resource			X	X	X										X	X	X	X	X	X	X	X	X										X	X	X	X	X	X	X	X	X				X	X	X
Supplier Prequalification						X	X	X							X	X	X							X	X	X	X	X	X				X	X	X	X	X	X				X	X	X	X	X	X
ICTs									X	X	X							X	X	X				X	X	X				X	X	X	X	X	X				X	X	X	X	X	X	X	X	X
Training and teambuilding												X	X	X							X	X	X				X	X	X	X	X	X				X	X	X	X	X	X	X	X	X	X	X	X
Decentralized decision-making	X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X		X	X
Partnership		X			X			X			X			X			X			X			X			X			X			X			X			X			X			X			X

Regression analysis was conducted between project schedule deviation and vulnerability under each level of adaptive capacity. As shown in Table 5-15, under the same level of adaptive capacity, there is a positive linear correlation between project vulnerability and schedule deviation. It means that under the same level of adaptive capacity, the greater the project vulnerability, the greater the schedule deviation under uncertainty. It is also observed that the coefficient of the linear relationship between project schedule deviation and vulnerability decrease with an increase in adaptive capacity. As shown in the last graph of Figure 5-18, when the levels of project adaptive capacity are lower (i.e., L1 and L2), the slopes of the linear regression fitting lines are greater. It means that, when the project adaptive capacity is at a lower level, the project schedule deviation under uncertainty is more sensitive to the changes in project vulnerability.

When comparing the project schedule deviation under the same level of vulnerability and different levels of adaptive capacity in the last graph of Figure 5-18, it is obvious that there is a negative correlation between project schedule deviation and adaptive capacity. Under the same level of vulnerability, the greater the adaptive capacity, the less significant the impacts of uncertainty on project schedule performance. The significance of the impact of project adaptive capacity on project schedule deviation is greater when project vulnerability is higher.

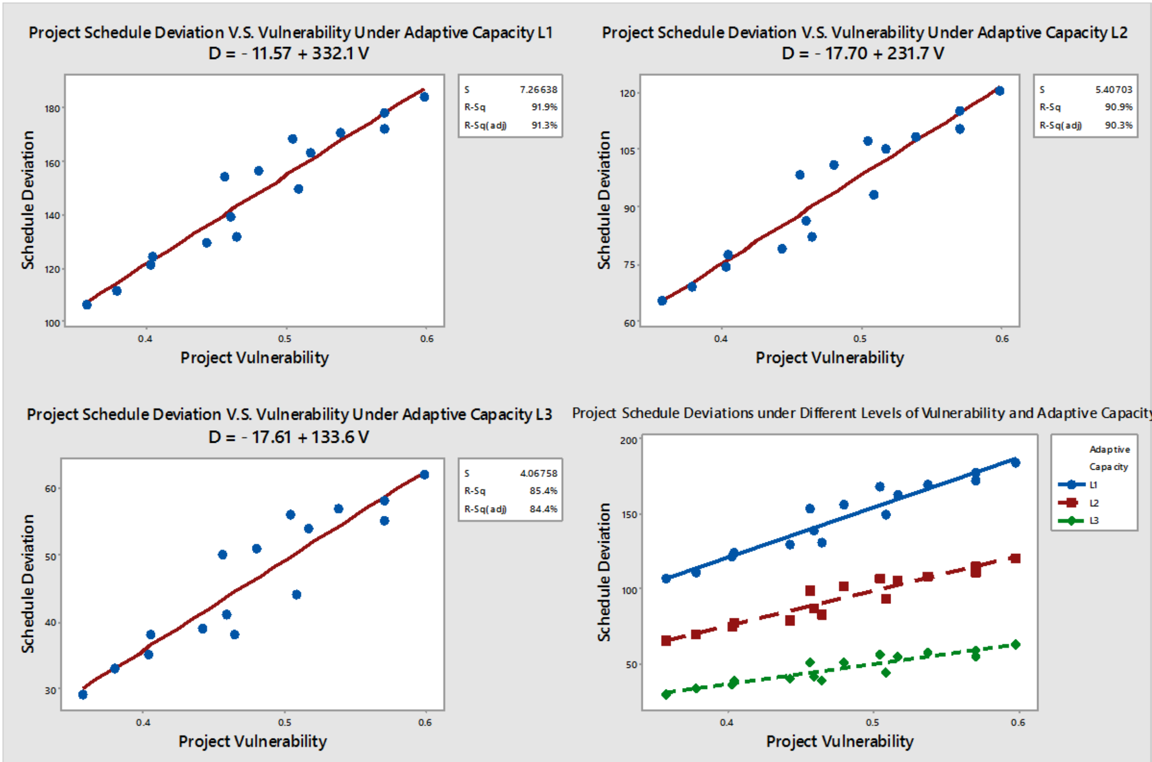


Figure 5-18 Project Vulnerability, Adaptive Capacity, and Schedule Deviation across Simulation Scenarios in Case 1

Table 5-15 Regression Analysis Results in Case 1

Adaptive Capacity	Linear Regression Results (D: schedule deviation; V: vulnerability)	R-Sq
L1	D=-11.57+332.1V	91.9%
L2	D=-17.70+231.7V	90.9%
L3	D=-17.61+133.6V	85.4%

Similar trends and relationships were observed in simulation results of case 2 and case 3.Figure 5-19 and Table 5-16 show the simulation results in case 2. Figure 5-20 and Table 5-17 show the simulation results in case 3.

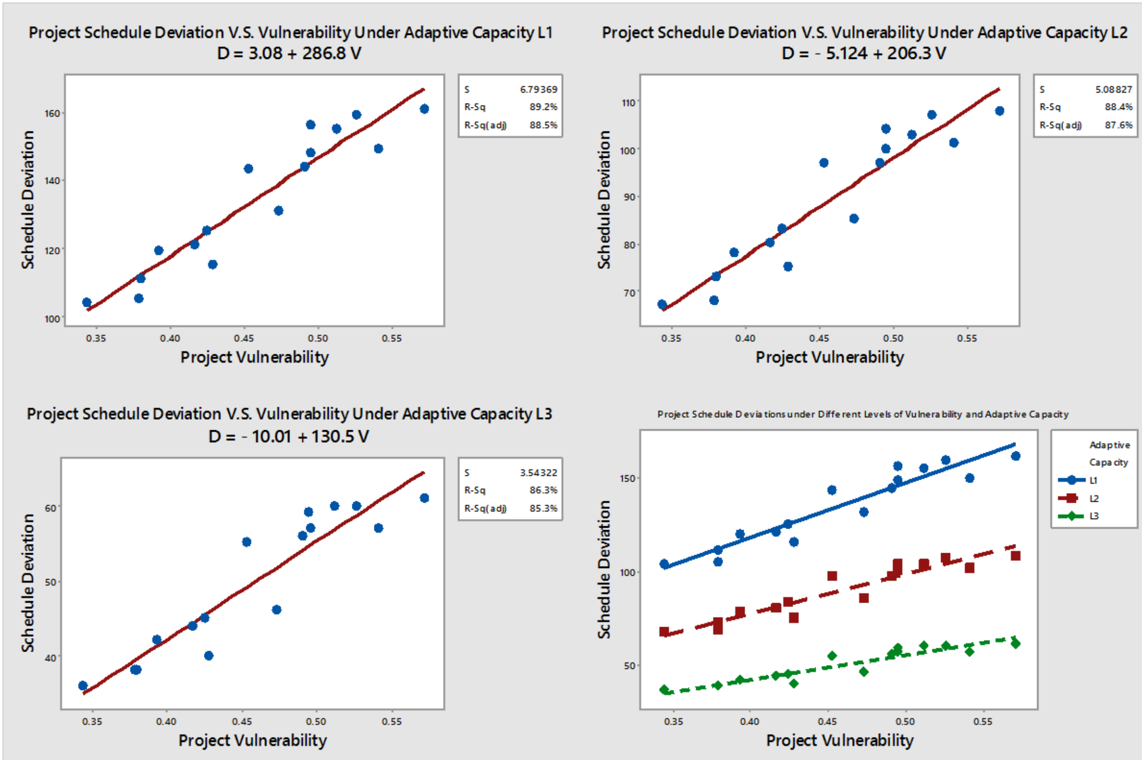


Figure 5-19 Project Vulnerability, Adaptive Capacity, and Schedule Deviation across Simulation Scenarios in Case 2

Table 5-16 Regression Analysis Results in Case 2

Adaptive Capacity	Linear Regression Results (D: schedule deviation; V: vulnerability)	R-Sq
L1	D=3.08+286.8V	89.2%
L2	D=-5.124+206.3V	88.4%
L3	D=-10.01+130.5V	86.3%

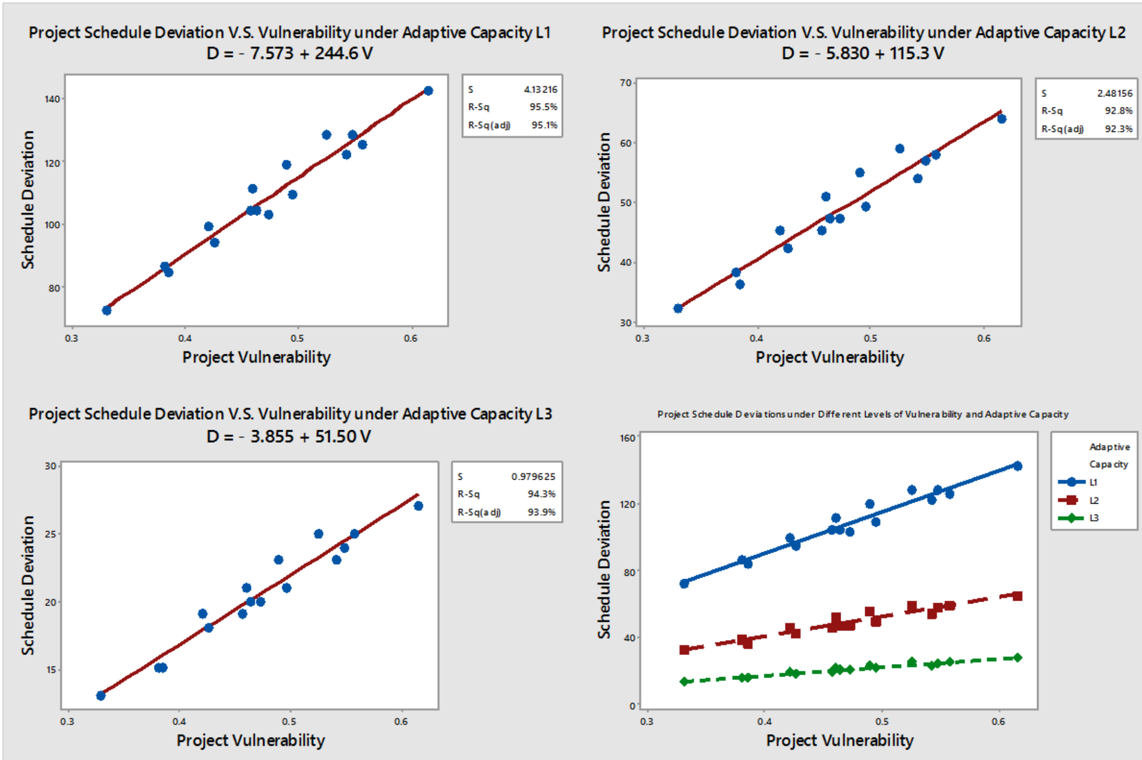


Figure 5-20 Project Vulnerability, Adaptive Capacity, and Schedule Deviation across Simulation Scenarios in Case 3

Table 5-17 Regression Analysis Results in Case 3

Adaptive Capacity	Linear Regression Results (D: schedule deviation; V: vulnerability)	R-Sq
L1	D=-7.573+244.6V	95.5%
L2	D=-5.830+115.3V	92.8%
L3	D=-3.855+51.50V	94.3%

The findings related to project vulnerability, adaptive capacity and project schedule deviation inform decision-making two approaches to mitigate the negative impacts of uncertainty: (1) Reduce project vulnerability. This approach is more effective and critical when project adaptive capacity is already at a low level; (2) Enhance project adaptive capacity. This approach is more effective and critical when project vulnerability is already at a high level.

5.4.3 Effectiveness of different planning strategies

Theoretical constructs related to the effectiveness of planning strategies identified in the simulation experiments across three cases are as follows:

Theoretical construct 3a: The effectiveness of a single planning strategy in mitigating negative impacts of uncertainty is different in different projects.

Theoretical construct 3b: There is a diminishing effect when adopting multiple planning strategies.

This set of theoretical constructs were built by analyzing the simulation results of project schedule deviation under different planning scenarios as defined in Table 5-14. The effectiveness (E) of a planning scenario (a single planning strategy or a combination of planning strategies) can be assessed using Equation 5.1:

$$E = (D_{BS} - D_S)/D_{BS} \tag{5.1}$$

Where D_{BS} is the average schedule deviation under uncertainty in the base scenario of a project system, while D_S is the average schedule deviation under uncertainty in the assessed scenario.

Using the simulation results, the effectiveness of each planning scenario in case 1, 2 and 3 was calculated. The effectiveness results in each case are shown in Figure 5-21, Figure 5-22, and Figure 5-23.

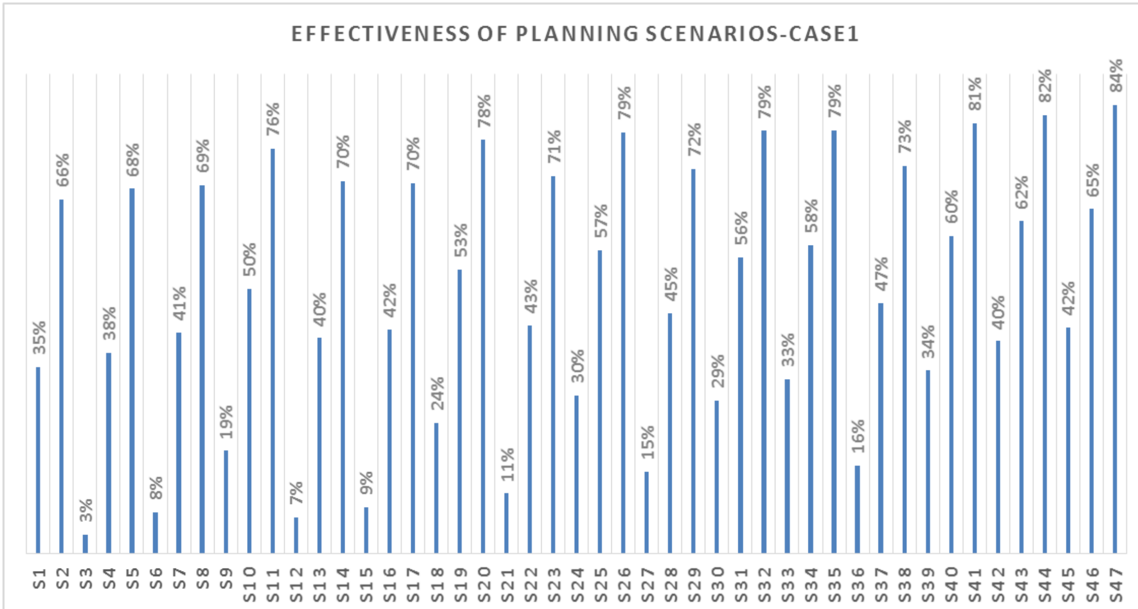


Figure 5-21 Effectiveness of Planning Scenarios in Case 1

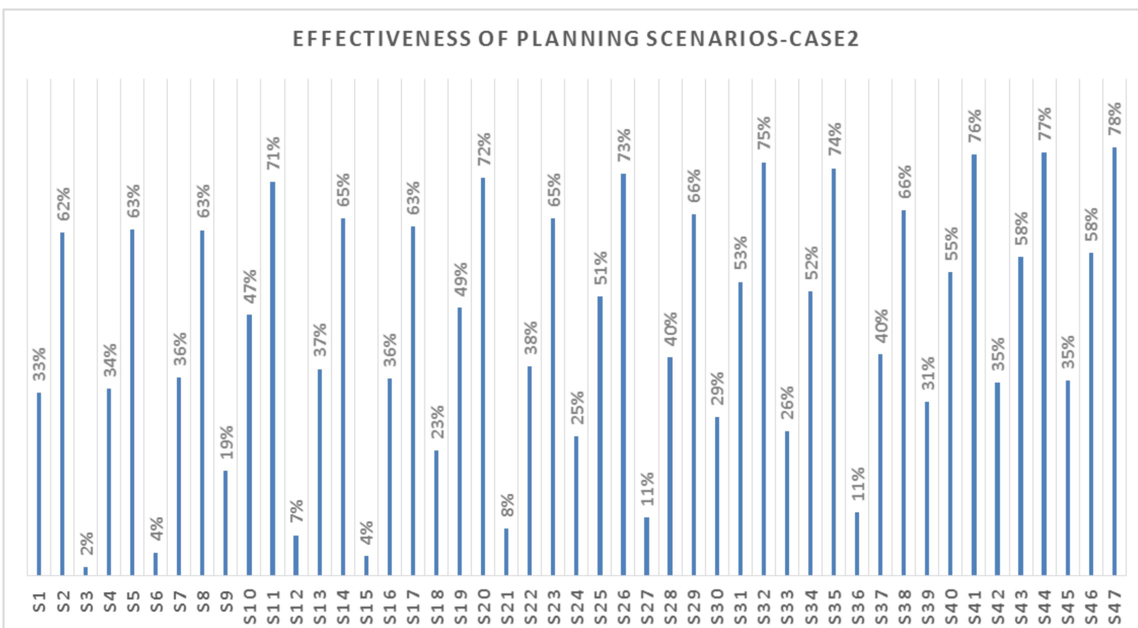


Figure 5-22 Effectiveness of Planning Scenarios in Case 2

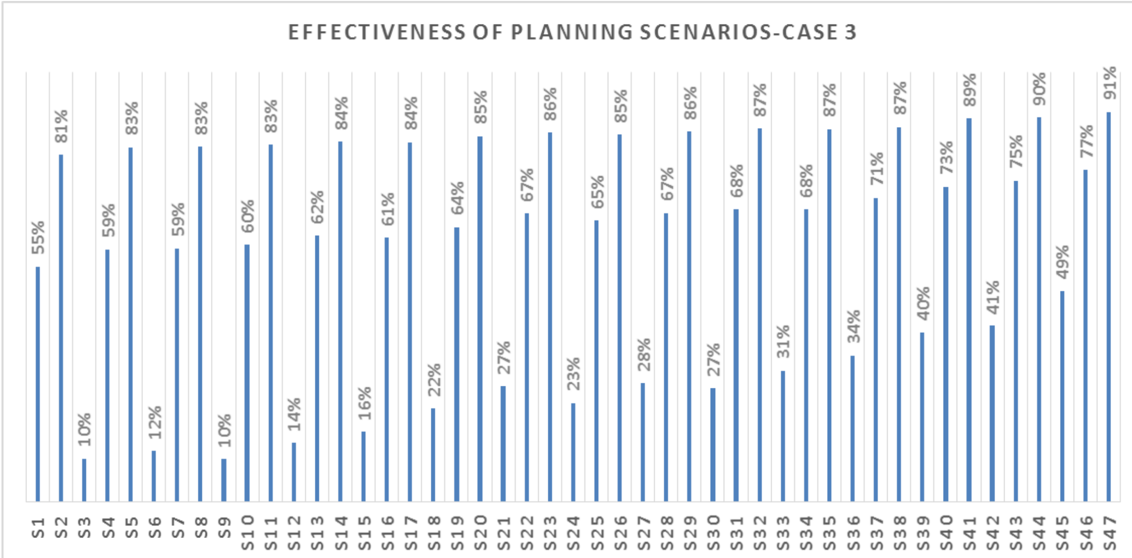


Figure 5-23 Effectiveness of Planning Scenarios in Case 3

From Figure 5-21, Figure 5-22, and Figure 5-23, first, the effectiveness of each single planning strategy in each case study was captured (Table 5-18). As shown in Table 5-18, the most effective planning strategy in all three cases is decentralized decision-making, followed by subcontractor partnership. These two planning strategies are related to enhancement of project adaptive capacity. In general, they are more effective than other planning strategies related to reducing project vulnerability. This is because planning strategies related to reducing project vulnerability usually only deal with one aspect of uncertainty (e.g., reducing information-related uncertainty, or reducing resource-related uncertainty), while enhancement of adaptive capacity can increase project recovery speed and capability in the face of all types of uncertainties. Although decentralized decision-making and subcontractor partnerships are the two most effective planning strategies in all three cases, their effectiveness values vary across cases. For example, the effectiveness of decentralized decision-making is 35% and 33% in case 1 and 2 respectively. However, in case 3, the effectiveness of decentralized decision-making has a value as high as 55%. The varying effects of planning strategies in different cases are more obvious with planning strategies related to vulnerability reduction. For example, as shown in Table 5-18, the most effective planning strategy via reducing project vulnerability in case 1 is adoption of ICTs for communication (19%), followed by conducting supplier prequalification (8%). In case 2, the most effective planning strategy via reducing project vulnerability is still adoption of ICTs (19%), while the second most effective planning strategy via reducing vulnerability is training and teambuilding (7%) instead. In case 3, the most effective planning strategy related to vulnerability is training and teambuilding (14%), followed by supplier prequalification (12%). It is shown that the effects of different planning strategies are different in different cases based on the traits of specific projects and the uncertain environments in which they operate.

Table 5-18 Effectiveness of Single Strategy in Each Case

Effectiveness	Case 1	Case 2	Case 3
Redundancy in resources	3%	2%	10%
Supplier prequalification	8%	4%	12%
ICTs	19%	19%	10%
Training and teambuilding	7%	7%	14%
Decentralized decision-making	35%	33%	55%
Subcontractor partnership	31%	29%	26%

Another observation, which is theoretical construct 3b, is that although the effectiveness is higher when adopting more planning strategies, there is a diminishing effect when adopting multiple planning strategies. In other words, the effectiveness of a planning scenario with multiple planning strategies is less than the cumulative value of effectiveness of all planning strategies adopted. A simple illustrative example of this phenomenon is given in Table 5-19. In case 2, the effectiveness of redundancy in resource is 2%. The effectiveness of adoption of ICTs is 19%. The effectiveness of decentralized decision-making is 33%. The sum of the effectiveness of all three planning strategies is 54%. However, when adopting these three planning strategies in case 2 as scenario 19, the effectiveness obtained from simulation is only 49%, which is 5% less than the sum value. Similar phenomena were observed in almost all multi-strategy scenarios in all three cases.

Table 5-19 Effectiveness of Selected Scenarios in Case 2

Scenarios	Effectiveness of Planning Strategies	
S3	Redundancy in resource	2%
S9	ICTs	19%
S1	Decentralized decision-making	33%
Sum of Effectiveness		54%
S19	Redundancy in resource + ICTs + Decentralized decision-making	49%

The findings related to effectiveness of planning strategies provide important information to project managers and decision makers who select planning strategies in pre-planning phase. First, the findings suggest that a project-specific approach needs to be used in planning. Project decision makers need to identify the most effective planning strategies for specific projects based on the project traits and uncertain environments in which they operate. Second, the findings inform project managers and decision makers that it is not always necessary to adopt all the planning strategies. Since there is a diminishing effect when adopting multiple planning strategies, project managers and decision makers should find an optimal combination of planning strategies based on the availability of resources.

5.5 Validation

The validity of theoretical constructs in this research was achieved through comparison of findings in other studies in the context of different systems. For example, Prater, Biehl, & Smith (2001) found out that the vulnerability in supply chain systems can be managed by reducing exposure to uncertainty and complexity. Their findings are consistent with the first set of theoretical constructs related to exposure to uncertainty, complexity and vulnerability in construction project systems built in this research. Dalziell & McManus (2004) pointed out that resilience in engineering systems can be enhanced by increasing the adaptive capacity of the systems, as well as reducing the vulnerability to hazard events. These findings are consistent with the second set of theoretical constructs related to the relationships between project vulnerability, adaptive capacity, and schedule deviation as an indicator of project resilience in this research. Finally, existing studies in project management field (Shenhar, 2001; Shenhar, Tishler, Dvir, Lipovetsky, & Lechler, 2002) have already identified the importance of applying project-specific planning strategies based on project characteristics, which is consistent with the third set of theoretical constructs related to the effectiveness of planning strategies built in this research.

5.6 Conclusions

The dynamic meta-network framework proposed in this chapter provides a novel approach for predictive and quantitative assessment of project resilience and performance outcomes under uncertainty. The proposed framework enabled: (1) predictive assessment of project performance under uncertainty based on investigation of dynamic interdependencies between various entities in project meta-networks; (2) quantitative evaluation of planning strategies in terms of their effectiveness in mitigating the negative impacts of uncertainty on project performance. The predictive assessment is critical for identifying and prioritizing effective planning strategies in order to optimize the allocation of resources for reducing the impacts of uncertainty on project performance. In addition, the proposed framework enabled investigation of the impacts of two project emergent properties (i.e., vulnerability and adaptive capacity) on project resilience and performance outcomes. The identified theoretical constructs lead to a better understanding of different concepts in project systems (e.g., complexity, uncertainty, vulnerability, adaptive capacity, resilience, and planning strategies) and facilitate integrated assessment of construction project performance under uncertainty.

6. CONCLUSIONS

6.1 Summary

Majorities of existing studies in the field of construction project performance assessment under uncertainty follow risk-based approaches, in which the focus is risk identification, mitigation and transfer. The risk-based approaches can reduce the chances of failure in environments with known risks. However, they cannot help design resilient projects which can survive in any unknown and uncertain environments. Thus, the goal of this research is to facilitate a paradigm shift from risk-based approaches to resilience-approaches by filling the knowledge gap related to resilience theory in the context of construction project systems.

Specifically, three research objectives related to project resilience were proposed as: (1) Understand and quantify project vulnerability based on exposure to uncertainty and project complexity; (2) Understand and quantify the impacts of project vulnerability and adaptive capacity on project resilience and schedule performance under uncertainty; and (3) Evaluate the effectiveness of planning strategies in enhancing project resilience.

To accomplish the research objectives, different studies were conducted and presented in different chapters in this dissertation. The major contributions and findings of each chapter in this dissertation, except Chapter 1 (Introduction) and Chapter 6 (Conclusions), are summarized in Table 6-1. Chapter 2 and 3 established frameworks to better conceptualize project systems and understand different theoretical concepts related to resilience. Based on the theoretical foundations established in these two chapters, a simulation framework was developed in Chapter 4 using theoretical underpinnings from network science. Using the simulation framework, three case studies were conducted in Chapter 5. Based on the simulation results, theoretical constructs related to different elements of project resilience were built. Accordingly, the three research objectives were achieved.

Table 6-1 Summary of Findings and Contributions of Chapters

Chapter	Contributions	Findings
2	Development of a project SoS conceptual framework	Projects are SoS aggregated from interconnected base-level entities (i.e., human agents, resources, and information). The traits and interdependencies of base-level entities greatly affect project performance.
3	Identification of project emergent properties affecting projects' ability in coping with complexity and uncertainty	A project's ability in coping with complexity and uncertainty can be understood and investigated based on different emergent properties, such as absorptive capacity, adaptive capacity and restorative capacity. Different planning strategies can lead to the enhancement of these emergent properties.
4	Creation of a meta-network simulation model	Project systems can be simulated as meta-networks consisting of different human agent, resource, information and task nodes. The impacts of uncertainty are translated as perturbations in project meta-networks. Emergent properties and project performance under uncertainty can be captured and assessed accordingly.
5	Building theoretical constructs related to resilience through case studies	Project resilience is positively correlated with adaptive capacity and negatively correlated with vulnerability. Project vulnerability can be mitigated through reducing exposure to uncertainty and complexity. Project adaptive capacity can be enhanced through increasing recovery speed and capabilities. Different planning strategies can enhance resilience either by reducing vulnerability or enhancing adaptive capacity. The effectiveness of planning strategies is project-specific, and has a diminishing effect.

6.2 Contributions

The contributions of this research are twofold. First, this research advances the science of resilience in construction projects. Second, the theoretical constructs can be used by decision-makers and practitioners to better manage their projects in uncertain environments.

6.2.1 Theoretical contributions

First, this research created the theory of resilience in complex construction projects. Development of the theory of resilience is emerging in the literature for better assessment of performance in systems. However, our understanding of resilience in construction project systems is rather limited. Through this research, a better understanding of different theoretical elements related to resilience (e.g., complexity, vulnerability, adaptive capacity) was obtained. Also, a simulation approach for quantitative assessment of project vulnerability, adaptive capacity and resilience was developed. Thus, this research filled the important gap in knowledge pertaining to project resilience.

Second, this study facilitated a paradigm shift toward proactive performance assessment in construction projects. Despite an abundance of studies on performance assessment in construction projects, most of the previous studies provide descriptive findings and one-size-fits-all strategies that lead to reactive approaches in assessment and management of performance in construction projects. This study created theoretical constructs for a better understanding of the links between planning strategies, complexity, vulnerability, adaptive capacity and resilience in construction projects. These constructs provide prescriptive findings and flexible strategies that lead to proactive assessment and management of performance in construction projects.

Third, based on the project system-of-systems conceptualization, this research addressed an important and yet unexplored aspect of performance assessment in construction projects, which is consideration of emergent properties. Similar to other complex systems, capturing the emergent properties in complex construction project systems is critical for gaining a better understanding of the integrative and dynamic behaviors of project systems. However, there are very limited studies in the existing literature pertaining to emergent properties in construction project systems. The SoS conceptualization and findings pertaining to resilience-related emergent properties in this research highlight the significance of considering emergent properties in project systems. Also, the SoS framework and methodology created in this research can be used for future investigation of other important emergent properties of project systems.

The last main scholarly contribution of this research is its adoption of a simulation approach for theory development in construction research. Simulation has been mainly used in construction research for creating tools for planning analysis and decision-making. Given the unique characteristics of construction research, in which there are inherent limitations for creating new theories due to the constraints related to conducting empirical experiments, the use of simulation approaches could lead to significant new theories in various areas. This study highlights the potential and provides an example for the implementation of simulation-based approaches in construction research.

6.2.2 Practical contributions

The models and theoretical constructs created in this research could significantly enhance the ability of decision-makers and practitioners in construction project planning and management. The findings in this research facilitate a paradigm shift toward prescriptive findings and flexible strategies that lead to proactive assessment and management of performance in construction projects considering the impacts of uncertainty. Specifically, practitioners could use the theoretical constructs identified in this research to:

(1) Assess and mitigate project vulnerability predictively. The theoretical constructs built in this research inform that project vulnerability is affected by the level of exposure to uncertainty and project complexity. Practitioners can use the simulation models developed in this research to assess the level of vulnerability in their own projects and then consider mitigating vulnerability by reducing exposure to uncertainty or project complexity if needed.

(2) Assess project schedule deviation predictively based on project vulnerability and adaptive capacity. The theoretical constructs built in this research inform that project schedule deviation, which is a measure of resilience, is correlated with project vulnerability and adaptive capacity. Practitioners can use the simulation models developed in this research to predictively assess the possible schedule deviation under uncertainty based on the level of vulnerability and adaptive capacity in their own projects. Based on the schedule deviation prediction, the practitioners can then consider enhancing project resilience either by mitigating vulnerability or increasing adaptive capacity in order to reduce the negative impacts of uncertainty on project performance.

(3) Select an optimal combination of planning strategies based on project traits in pre-planning phase. Enhancement of project resilience is ultimately realized by adopting planning strategies in projects. The theoretical constructs built in this

research inform that different planning strategies have varying effects on different projects based on the characteristics of the projects. Also, the effectiveness of planning strategies diminishes when multiple planning strategies are adopted. Practitioners can use the simulation models developed in this research to test the effectiveness of specific planning strategies in their projects and then select an optimal combination of planning strategies which best serve their needs. In addition, based on the observations in this research, planning strategy selection based on qualitative analysis of project traits is also achievable without developing and running computational models.

Although this research was conducted in the context of complex construction projects, the theoretical constructs created in this research could also be adopted in enhancing resilience and project performance in other disciplines and industries (e.g., pharmaceutical and IT projects) that face significant uncertainty and complexity.

6.3 Limitations and Future Work

There are some limitations in this research, which should be addressed in future studies. First, project schedule performance was selected as the only performance indicator in this research. Project schedule deviation was used as a measure of resilience. In future studies, other important performance indicators including cost, quality and safety can be incorporated into consideration. Cost-benefit analysis of planning strategies to enhance resilience also can be conducted when cost is included as a performance indicator.

Second, there are some simplified assumptions in the conceptual framework of this research. For example, the project meta-networks developed in this study are not weighted networks. However, in real world, the links between human agents, resources, information, and tasks may have different importance weights. Another related assumption is that since project meta-networks are binary networks, the impacts of uncertain events on project meta-networks are translated into complete removal of certain nodes and links. However, different uncertain events may have different levels of impacts on project meta-networks which can cause partial disruptions in the meta-networks. In future studies, weighted networks can be considered to better address these limitations.

Third, this study utilized a new approach and methodology to investigate resilience quantitatively in the context of construction project systems. Theoretical constructs were built from observations in three case studies of commercial projects. In future studies, more case studies across different project types need to be conducted to further test the proposed framework and validate the theoretical constructs.

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APPENDIX

(1) Code for Monte Carlo Simulation for Vulnerability Assessment of Case Study 1 in Base Scenario

```
for a=1:1000
    AI=[1,1,1,1,1,1;
        1,1,1,1,1,1;
        1,1,0,0,0,0;
        1,1,1,1,1,0;
        1,1,1,1,1,0;
        1,1,1,1,1,0;
        1,1,1,1,1,0;
        1,1,1,1,1,0;
        1,1,0,1,1,1;
        1,1,0,1,1,1;
        1,1,0,1,1,1;
        1,1,0,1,0,1];
     AR=[0,0,0,0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0,0,0,0;
         1,1,1,0,1,1,0,0,0,0,0,0,0,0,0;
         0,0,0,1,1,1,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,1,1,1,1,1,0,0,0,0,0,0;
         0,0,0,0,1,1,0,0,0,0,0,0,1,1,0;
         0,0,0,0,0,0,0,0,0,0,0,0,0,0,1;
         0,0,0,0,1,1,0,0,0,1,0,0,0,0,0;
         0,0,0,0,1,1,0,0,0,0,1,0,0,0,0;
         0,0,0,0,1,1,0,0,0,0,0,1,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0,0,0,0];
     AT=[0,0,0,1,0,0,0,0,0,0,0,1;
         0,0,1,1,0,0,0,0,0,0,0,1;
         1,1,0,0,0,0,0,0,0,0,0,0;
         0,0,1,1,1,0,0,0,0,0,0,0;
         0,0,0,1,0,0,0,0,0,0,0,0;
         0,0,0,1,0,1,1,1,0,0,0,0;
         0,0,0,1,0,0,0,0,0,0,1,0;
         0,0,1,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,1,0,0;
         0,0,0,0,0,0,0,0,0,1,0,0;
         0,0,0,0,0,0,0,0,0,1,0,0;
         0,0,0,0,0,0,0,0,0,0,0,1];
     IT=[1,1,1,1,1,1,1,1,1,1,1,1;
         1,1,1,1,1,1,1,1,1,1,1,1;
         0,0,0,1,0,0,0,0,0,0,0,0;
         0,0,0,0,1,1,1,1,1,1,1,1;
         0,0,0,0,1,1,1,1,1,1,1,0;
         0,0,0,0,0,0,0,0,1,0,1];
     RT=[1,0,0,0,0,0,0,0,0,0,0,0;
         0,1,0,0,0,0,0,0,0,0,0,0;
         0,1,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,1,0,0,0,0,0,0,0;
         0,0,0,0,1,1,0,0,0,0,1,0;
         0,0,0,0,1,1,0,0,0,0,1,0;
         0,0,0,0,0,1,0,0,0,0,0,0;
```

```
        0,0,0,0,0,0,1,0,0,0,0;
        0,0,0,0,0,0,0,1,0,0,0;
        0,0,0,0,0,0,0,0,1,0,0;
        0,0,0,0,0,0,0,0,1,0,0;
        0,0,0,0,0,0,0,0,1,0,0;
        0,0,0,0,0,0,0,0,0,1,0;
        0,0,0,0,0,0,0,0,0,1,0;
        0,0,1,0,0,0,0,0,0,0,0];
p_h=0.2305;
p_i=0.352;
p_r=0.316;
h=size(AT,1);                 % number of human agents
uh=rand(1, h) < p_h;          % generate a random vector of human agent
availablity based on the level of uncertainty p_h.
r=1;
while r<=h                    % reflect the impact on matrix AI and AR
    if uh(1,r)==1
       AI(r,:)=0;
       AR(r,:)=0;
    end
    r=r+1;
end
i=size(IT,1);                 % number of information
ui=rand(1, i) < p_i;          % generate a random vector of information
availablity based on the level of uncertainty p_i.
r=1;
while r<=i                    % reflect the impact on matrix AI
    if ui(1,r)==1
       AI(:,r)=0;
    end
    r=r+1;
end
re=size(RT,1);                 % number of resources
ur=rand(1, re) < p_r;          % generate a random vector of resource
availablity based on the level of uncertainty p_r.
r=1;
while r<=re                    % reflect the impact on matrix AR
    if ur(1,r)==1
       AR(:,r)=0;
    end
    r=r+1;
end
% calculation of number of tasks cannot be implemented due to lack of
% information
supplyinfo=((AT).')*(AI);        % information supply matrix
requireinfo=(IT).';              % informatiion requirement matrix
infogap=supplyinfo-requireinfo;  % information gap matrix
n=size(infogap,1);               % number of rows in information gap
matrix
fi=0;                            % original number of failed tasks is 0
r=1;                             % original row number is 1
while r<=n                       % check each row in information gap
matrix
    if any(infogap(r,:)==-1)     % task i fails if any element in row i
is -1
```

```
        fi=fi+1;
    end
    r=r+1;
end
% calculation of number of tasks cannot be implemented due to lack of
% resource
supplyresource=((AT).')*(AR);
requireresource=(RT).';
resourcegap=supplyresource-requireresource;
m=size(resourcegap,1);
fr=0;
r=1;
while r<=m
    if any(resourcegap(r,:)==-1)
        fr=fr+1;
    end
    r=r+1;
end
% calculation of meta-network efficiency
tasknumber=length(AT);
e=((tasknumber-fi)/tasknumber+(tasknumber-fr)/tasknumber)/2;
output(a)=1-e;
end
```

(2) Code for Monte Carlo Simulation for Schedule Deviation Assessment of Case Study 1 in Base Scenario

```
for a=1:1000
d_hh=21; d_mh=14; d_lh=3;       % define human-agent related delay days
d_hr=21; d_mr=14; d_lr=12;      % define resource related delay days
d_hi=28; d_mi=14; d_li=7;       % define information related delay days
h=12;                    % number of human agents
i=6;                    % number of information
r=15;                   % number of resources
t=0;
uhh=0.05;               % probability of high-disturbance human disruption
umh=0.1;                % probability of medium-disturbance human disruption
ulh=0.1;                % probability of low-disturbance human disruption
uhr=0.05;              % probability of high-disturbance resource disruption
umr=0.1;            % probability of medium-disturbance resource disruption
ulr=0.2;            % probability of low-disturbance resource disruption
uhi=0.1;            % probability of high-disturbance resource disruption
umi=0.1;            % probability of medium-disturbance resource disruption
uli=0.2;            % probability of low-disturbance resource disruption
% task 1
uh=rand(1, h) < (1-uhh);
if uh(3)==0
    d1_1=d_hh;
else d1_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(3)==0
    d1_2=d_mh;
else d1_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(3)==0
    d1_3=d_lh;
else d1_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(2)==0
    d1_4=d_hi;
else d1_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0
    d1_5=d_mi;
else d1_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0
    d1_6=d_li;
else d1_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(1)==0
```

```
    d1_7=d_hr;
else d1_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(1)==0
    d1_8=d_mr;
else d1_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(1)==0
    d1_9=d_lr;
else d1_9=0;
end
D=[d1_1,d1_2,d1_3,d1_4,d1_5,d1_6,d1_7,d1_8,d1_9];
d1=max(D);
t=t+14+d1;
% task 2
uh=rand(1, h) < (1-uhh);
if uh(3)==0
    d2_1=d_hh;
else d2_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(3)==0
    d2_2=d_mh;
else d2_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(3)==0
    d2_3=d_lh;
else d2_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(2)==0
    d2_4=d_hi;
else d2_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0
    d2_5=d_mi;
else d2_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0
    d2_6=d_li;
else d2_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(2)==0||ur(3)==0
    d2_7=d_hr;
else d2_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(2)==0||ur(3)==0
    d2_8=d_mr;
```

```
else d2_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(2)==0||ur(3)==0
    d2_9=d_lr;
else d2_9=0;
end
D=[d2_1,d2_2,d2_3,d2_4,d2_5,d2_6,d2_7,d2_8,d2_9];
d2=max(D);
t=t+14+d2;
% task 3
uh=rand(1, h) < (1-uhh);
if uh(2)==0||uh(4)==0||uh(8)==0
    d3_1=d_hh;
else d3_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(2)==0||uh(4)==0||uh(8)==0
    d3_2=d_mh;
else d3_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(2)==0||uh(4)==0||uh(8)==0
    d3_3=d_lh;
else d3_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(2)==0
    d3_4=d_hi;
else d3_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0
    d3_5=d_mi;
else d3_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0
    d3_6=d_li;
else d3_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(15)==0
    d3_7=d_hr;
else d3_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(15)==0
    d3_8=d_mr;
else d3_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(15)==0
    d3_9=d_lr;
else d3_9=0;
```

```
end
D=[d3_1,d3_2,d3_3,d3_4,d3_5,d3_6,d3_7,d3_8,d3_9];
d3=max(D);
t=t+2+d3;
% task 4
uh=rand(1, h) < (1-uhh);
if uh(1)==0||uh(2)==0||uh(4)==0||uh(5)==0||uh(6)==0||uh(7)==0
    d4_1=d_hh;
else d4_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(1)==0||uh(2)==0||uh(4)==0||uh(5)==0||uh(6)==0||uh(7)==0
    d4_2=d_mh;
else d4_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(1)==0||uh(2)==0||uh(4)==0||uh(5)==0||uh(6)==0||uh(7)==0
    d4_3=d_lh;
else d4_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(2)==0||ui(3)==0
    d4_4=d_hi;
else d4_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0||ui(3)==0
    d4_5=d_mi;
else d4_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0||ui(3)==0
    d4_6=d_li;
else d4_6=0;
end
D=[d4_1,d4_2,d4_3,d4_4,d4_5,d4_6];
d4=max(D);
t=t+21+d4;
% task 5
uh=rand(1, h) < (1-uhh);
if uh(4)==0
    d5_1=d_hh;
else d5_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(4)==0
    d5_2=d_mh;
else d5_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(4)==0
    d5_3=d_lh;
else d5_3=0;
end
ui=rand(1,i) < (1-uhi);
```

```
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d5_4=d_hi;
else d5_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d5_5=d_mi;
else d5_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d5_6=d_li;
else d5_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(4)==0||ur(5)==0||ur(6)==0
    d5_7=d_hr;
else d5_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(4)==0||ur(5)==0||ur(6)==0
    d5_8=d_mr;
else d5_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(4)==0||ur(5)==0||ur(6)==0
    d5_9=d_lr;
else d5_9=0;
end
D=[d5_1,d5_2,d5_3,d5_4,d5_5,d5_6,d5_7,d5_8,d5_9];
d5=max(D);
t=t+14+d5;
% task 6
uh=rand(1, h) < (1-uhh);
if uh(6)==0
    d6_1=d_hh;
else d6_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(6)==0
    d6_2=d_mh;
else d6_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(6)==0
    d6_3=d_lh;
else d6_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d6_4=d_hi;
else d6_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
```

```
    d6_5=d_mi;
else d6_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d6_6=d_li;
else d6_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(5)==0||ur(6)==0||ur(7)==0
    d6_7=d_hr;
else d6_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(5)==0||ur(6)==0||ur(7)==0
    d6_8=d_mr;
else d6_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(5)==0||ur(6)==0||ur(7)==0
    d6_9=d_lr;
else d6_9=0;
end
D=[d6_1,d6_2,d6_3,d6_4,d6_5,d6_6,d6_7,d6_8,d6_9];
d6=max(D);
t=t+10+d6;
% task 7
uh=rand(1, h) < (1-uhh);
if uh(6)==0
    d7_1=d_hh;
else d7_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(6)==0
    d7_2=d_mh;
else d7_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(6)==0
    d7_3=d_lh;
else d7_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d7_4=d_hi;
else d7_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d7_5=d_mi;
else d7_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d7_6=d_li;
```

```
else d7_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(8)==0
    d7_7=d_hr;
else d7_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(8)==0
    d7_8=d_mr;
else d7_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(8)==0
    d7_9=d_lr;
else d7_9=0;
end
D=[d7_1,d7_2,d7_3,d7_4,d7_5,d7_6,d7_7,d7_8,d7_9];
d7=max(D);
t=t+21+d7;
% task 8
uh=rand(1, h) < (1-uhh);
if uh(6)==0
    d8_1=d_hh;
else d8_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(6)==0
    d8_2=d_mh;
else d8_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(6)==0
    d8_3=d_lh;
else d8_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d8_4=d_hi;
else d8_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d8_5=d_mi;
else d8_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d8_6=d_li;
else d8_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(9)==0
    d8_7=d_hr;
else d8_7=0;
```

```
end
ur=rand(1,r) < (1-umr);
if ur(9)==0
    d8_8=d_mr;
else d8_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(9)==0
    d8_9=d_lr;
else d8_9=0;
end
D=[d8_1,d8_2,d8_3,d8_4,d8_5,d8_6,d8_7,d8_8,d8_9];
d8=max(D);
t=t+21+d8;
% task 9
uh=rand(1, h) < (1-uhh);
if uh(9)==0||uh(10)==0||uh(11)==0
    d9_1=d_hh;
else d9_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(9)==0||uh(10)==0||uh(11)==0
    d9_2=d_mh;
else d9_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(9)==0||uh(10)==0||uh(11)==0
    d9_3=d_lh;
else d9_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0||ui(6)==0
    d9_4=d_hi;
else d9_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0||ui(6)==0
    d9_5=d_mi;
else d9_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0||ui(6)==0
    d9_6=d_li;
else d9_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(10)==0||ur(11)==0||ur(12)==0
    d9_7=d_hr;
else d9_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(10)==0||ur(11)==0||ur(12)==0
    d9_8=d_mr;
else d9_8=0;
end
```

```
ur=rand(1,r) < (1-ulr);
if ur(10)==0||ur(11)==0||ur(12)==0
    d9_9=d_lr;
else d9_9=0;
end
D=[d9_1,d9_2,d9_3,d9_4,d9_5,d9_6,d9_7,d9_8,d9_9];
d9=max(D);
t=t+14+d9;
% task 10
uh=rand(1, h) < (1-uhh);
if uh(7)==0
    d10_1=d_hh;
else d10_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(7)==0
    d10_2=d_mh;
else d10_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(7)==0
    d10_3=d_lh;
else d10_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d10_4=d_hi;
else d10_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d10_5=d_mi;
else d10_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(5)==0
    d10_6=d_li;
else d10_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(5)==0||ur(6)==0||ur(13)==0||ur(14)==0
    d10_7=d_hr;
else d10_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(5)==0||ur(6)==0||ur(13)==0||ur(14)==0
    d10_8=d_mr;
else d10_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(5)==0||ur(6)==0||ur(13)==0||ur(14)==0
    d10_9=d_lr;
else d10_9=0;
end
D=[d10_1,d10_2,d10_3,d10_4,d10_5,d10_6,d10_7,d10_8,d10_9];
```

```
d10=max(D);
t=t+21+d10;
% task 11
uh=rand(1, h) < (1-uhh);
if uh(1)==0||uh(2)==0||uh(12)==0
    d11_1=d_hh;
else d11_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(1)==0||uh(2)==0||uh(12)==0
    d11_2=d_mh;
else d11_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(1)==0||uh(2)==0||uh(12)==0
    d11_3=d_lh;
else d11_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(6)==0
    d11_4=d_hi;
else d11_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(6)==0
    d11_5=d_mi;
else d11_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0||ui(4)==0||ui(6)==0
    d11_6=d_li;
else d11_6=0;
end
D=[d11_1,d11_2,d11_3,d11_4,d11_5,d11_6];
d11=max(D);
t=t+2+d11;
output(a)=t;
end
```

(3) Code for Monte Carlo Simulation for Vulnerability Assessment of Case Study 2 in Base Scenario

```
for a=1:1000
    AI=[1,1,1,1,1,1,1,0,0,0,0,1;
        1,1,1,1,1,0,0,0,0,0,0,0;
        1,1,1,1,1,0,0,0,0,0,0,0;
        1,1,0,1,0,0,0,0,0,0,0,0;
        1,1,0,0,1,0,0,0,0,0,0,0;
        1,1,1,1,1,1,1,1,1,1,1,1;
        1,1,1,1,1,1,1,1,1,1,1,1;
        1,1,1,1,1,1,0,1,1,1,1,1;
        0,1,1,1,1,1,1,1,0,0,0,1;
        0,1,1,0,0,1,1,0,1,0,0,0;
        0,1,1,0,1,1,1,0,0,1,0,0;
        0,1,1,1,1,1,1,0,0,0,1,0];
     AR=[0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,1,0,1,1,1,0,0,0,0,0;
         1,1,0,1,0,0,0,0,0,0,0,1;
         0,0,0,0,0,0,0,1,0,0,0,1;
         0,0,0,0,0,0,0,0,1,1,1,1];
     AT=[0,0,0,0,0,0,1,0,0,0,0,0,0;
         1,0,0,0,1,0,0,0,0,0,0,0,0;
         0,1,0,0,1,0,0,0,0,0,0,0,0;
         0,0,1,0,1,0,0,0,0,0,0,0,0;
         0,0,0,1,1,0,0,0,0,0,0,0,0;
         0,0,0,0,1,0,1,0,0,0,0,0,0;
         0,0,0,0,1,1,1,0,0,0,0,0,0;
         0,0,0,0,1,0,1,0,0,0,0,0,0;
         0,0,0,0,0,0,1,0,1,0,0,0,1;
         0,0,0,0,0,0,0,1,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,1,0,0,0;
         0,0,0,0,0,0,0,0,0,0,1,1,0];
     IT=[1,1,1,1,0,0,0,0,0,0,0,0,0;
         0,1,1,1,1,1,0,1,1,1,1,1,1;
         0,0,0,0,1,1,0,1,1,1,1,1,1;
         0,0,0,0,1,1,0,0,1,0,1,0,0;
         0,0,0,0,1,1,0,0,1,1,0,1,0;
         0,0,0,0,0,1,0,1,1,1,1,1,1;
         0,0,0,0,0,0,1,1,1,1,1,1,1;
         0,0,0,0,0,1,0,0,0,0,0,0,0;
         0,0,0,0,0,1,0,0,0,0,0,0,0;
         0,0,0,0,0,1,0,0,0,0,0,0,0;
         0,0,0,0,0,1,0,0,0,0,0,0,0;
         0,0,0,0,0,0,1,0,0,0,0,0,0];
     RT=[0,0,0,0,0,0,0,1,0,0,0,0,0;
```

```
          0,0,0,0,0,0,0,1,0,0,0,0,0;
          0,0,0,0,0,0,0,0,1,0,0,0,1;
          0,0,0,0,0,0,0,1,0,0,0,0,0;
          0,0,0,0,0,0,0,0,1,0,0,0,0;
          0,0,0,0,0,0,0,0,1,0,0,0,1;
          0,0,0,0,0,0,0,0,1,0,0,0,0;
          0,0,0,0,0,0,0,0,0,1,0,0,0;
          0,0,0,0,0,0,0,0,0,0,1,0,0;
          0,0,0,0,0,0,0,0,0,0,1,0,0;
          0,0,0,0,0,0,0,0,0,0,0,1,0;
          0,0,0,0,0,0,0,1,0,1,1,1,0];
p_h=0.2305;
p_i=0.352;
p_r=0.316;
h=size(AT,1);                 % number of human agents
uh=rand(1, h) < p_h;          % generate a random vector of human agent
availability based on the level of uncertainty p_h.
r=1;
while r<=h                    % reflect the impact on matrix AI and AR
    if uh(1,r)==1
       AI(r,:)=0;
       AR(r,:)=0;
    end
    r=r+1;
end
i=size(IT,1);                 % number of information
ui=rand(1, i) < p_i;          % generate a random vector of information
availability based on the level of uncertainty p_i.
r=1;
while r<=i                    % reflect the impact on matrix AI
    if ui(1,r)==1
       AI(:,r)=0;
    end
    r=r+1;
end
re=size(RT,1);                 % number of resources
ur=rand(1, re) < p_r;          % generate a random vector of resource
availability based on the level of uncertainty p_r.
r=1;
while r<=re                    % reflect the impact on matrix AR
    if ur(1,r)==1
       AR(:,r)=0;
    end
    r=r+1;
end
% calculation of number of tasks cannot be implemented due to lack of
% information
supplyinfo=((AT).')*(AI);       % information supply matrix
requireinfo=(IT).';             % information requirement matrix
infogap=supplyinfo-requireinfo; % information gap matrix
n=size(infogap,1);              % number of rows in information gap
matrix
fi=0;                           % original number of failed tasks is 0
r=1;                            % original row number is 1
```

```
while r<=n                          % check each row in information gap
matrix
    if any(infogap(r,:)==-1)     % task i fails if any element in row i
is -1
        fi=fi+1;
    end
    r=r+1;
end
% calculation of number of tasks cannot be implemented due to lack of
% resource
supplyresource=((AT).')*(AR);
requireresource=(RT).';
resourcegap=supplyresource-requireresource;
m=size(resourcegap,1);
fr=0;
r=1;
while r<=m
    if any(resourcegap(r,:)==-1)
        fr=fr+1;
    end
    r=r+1;
end
% calculation of meta-network efficiency
tasknumber=length(AT);
e=((tasknumber-fi)/tasknumber+(tasknumber-fr)/tasknumber)/2;
output(a)=1-e;
end
```

(4) Code for Monte Carlo Simulation for Schedule Deviation Assessment of Case Study 2 in Base Scenario

```
for a=1:1000
d_hh=21; d_mh=14; d_lh=3;       % define human-agent related delay days
d_hr=21; d_mr=14; d_lr=12;      % define resource related delay days
d_hi=28; d_mi=14; d_li=7;       % define information related delay days
h=12;                   % number of human agents
i=12;                   % number of information
r=12;                  % number of resources
t=0;                     % initial time
uhh=0.05;             % probability of high-disturbance human disruption
umh=0.1;              % probability of medium-disturbance human disruption
ulh=0.1;                 % probability of low-disturbance human disruption
uhr=0.05;            % probability of high-disturbance resource disruption
umr=0.1;            % probability of medium-disturbance resource disruption
ulr=0.2;            % probability of low-disturbance resource disruption
uhi=0.1;            % probability of high-disturbance resource disruption
umi=0.1;            % probability of medium-disturbance resource disruption
uli=0.2;            % probability of low-disturbance resource disruption
% task 1
uh=rand(1, h) < (1-uhh);
if uh(2)==0
    d1_1=d_hh;
else d1_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(2)==0
    d1_2=d_mh;
else d1_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(2)==0
    d1_3=d_lh;
else d1_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0
    d1_4=d_hi;
else d1_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0
    d1_5=d_mi;
else d1_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0
    d1_6=d_li;
else d1_6=0;
end
D=[d1_1,d1_2,d1_3,d1_4,d1_5,d1_6];
d1=max(D);
```

```
t=t+20+d1;
% task 2
uh=rand(1, h) < (1-uhh);
if uh(3)==0
    d2_1=d_hh;
else d2_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(3)==0
    d2_2=d_mh;
else d2_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(3)==0
    d2_3=d_lh;
else d2_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0 || ui(2)==0
    d2_4=d_hi;
else d2_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0|| ui(2)==0
    d2_5=d_mi;
else d2_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0 || ui(2)==0
    d2_6=d_li;
else d2_6=0;
end
D=[d2_1,d2_2,d2_3,d2_4,d2_5,d2_6];
d2=max(D);
t2=t+15+d2;
% task 3
uh=rand(1, h) < (1-uhh);
if uh(4)==0
    d3_1=d_hh;
else d3_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(4)==0
    d3_2=d_mh;
else d3_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(4)==0
    d3_3=d_lh;
else d3_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0 || ui(2)==0
    d3_4=d_hi;
else d3_4=0;
```

```
end
ui=rand(1,i) < (1-umi);
if ui(1)==0|| ui(2)==0
    d3_5=d_mi;
else d3_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0 || ui(2)==0
    d3_6=d_li;
else d3_6=0;
end
D=[d3_1,d3_2,d3_3,d3_4,d3_5,d3_6];
d3=max(D);
t3=t+10+d3;
% task 4
uh=rand(1, h) < (1-uhh);
if uh(5)==0
    d4_1=d_hh;
else d4_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(5)==0
    d4_2=d_mh;
else d4_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(5)==0
    d4_3=d_lh;
else d4_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0 || ui(2)==0
    d4_4=d_hi;
else d4_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0|| ui(2)==0
    d4_5=d_mi;
else d4_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0 || ui(2)==0
    d4_6=d_li;
else d4_6=0;
end
D=[d4_1,d4_2,d4_3,d4_4,d4_5,d4_6];
d4=max(D);
t4=t+10+d4;
MT=[t2, t3, t4];
t=max(MT);
% task 5
uh=rand(1, h) < (1-uhh);
if uh(2)==0||uh(3)==0||uh(4)==0||uh(5)==0||uh(6)==0||uh(7)==0||uh(8)==0
    d5_1=d_hh;
else d5_1=0;
```

```
end
uh=rand(1, h) < (1-umh);
if uh(2)==0||uh(3)==0||uh(4)==0||uh(5)==0||uh(6)==0||uh(7)==0||uh(8)==0
    d5_2=d_mh;
else d5_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(2)==0||uh(3)==0||uh(4)==0||uh(5)==0||uh(6)==0||uh(7)==0||uh(8)==0
    d5_3=d_lh;
else d5_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(5)==0
    d5_4=d_hi;
else d5_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(5)==0
    d5_5=d_mi;
else d5_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(5)==0
    d5_6=d_li;
else d5_6=0;
end
D=[d5_1,d5_2,d5_3,d5_4,d5_5,d5_6];
d5=max(D);
t=t+2+d5;
% task 6
uh=rand(1, h) < (1-uhh);
if uh(7)==0
    d6_1=d_hh;
else d6_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(7)==0
    d6_2=d_mh;
else d6_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(7)==0
    d6_3=d_lh;
else d6_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(5)==0|| ui(6)==0|| ui(8)==0||
ui(9)==0|| ui(10)==0|| ui(11)==0
    d6_4=d_hi;
else d6_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(5)==0|| ui(6)==0|| ui(8)==0||
ui(9)==0|| ui(10)==0|| ui(11)==0
    d6_5=d_mi;
```

```
else d6_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(5)==0|| ui(6)==0|| ui(8)==0||
ui(9)==0|| ui(10)==0|| ui(11)==0
    d6_6=d_li;
else d6_6=0;
end
D=[d6_1,d6_2,d6_3,d6_4,d6_5,d6_6];
d6=max(D);
t=t+5+d6;
% task 7
uh=rand(1, h) < (1-uhh);
if uh(1)==0|| uh(6)==0|| uh(7)==0|| uh(8)==0|| uh(9)==0
    d7_1=d_hh;
else d7_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(1)==0|| uh(6)==0|| uh(7)==0|| uh(8)==0|| uh(9)==0
    d7_2=d_mh;
else d7_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(1)==0|| uh(6)==0|| uh(7)==0|| uh(8)==0|| uh(9)==0
    d7_3=d_lh;
else d7_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(7)==0 || ui(12)==0
    d7_4=d_hi;
else d7_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(7)==0 || ui(12)==0
    d7_5=d_mi;
else d7_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(7)==0 || ui(12)==0
    d7_6=d_li;
else d7_6=0;
end
D=[d7_1,d7_2,d7_3,d7_4,d7_5,d7_6];
d7=max(D);
t=t+2+d7;
% task 8
uh=rand(1, h) < (1-uhh);
if uh(10)==0
    d8_1=d_hh;
else d8_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(10)==0
    d8_2=d_mh;
else d8_2=0;
```

```
end
uh=rand(1, h) < (1-ulh);
if uh(10)==0
    d8_3=d_lh;
else d8_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(2)==0 || ui(3)==0|| ui(6)==0|| ui(7)==0
    d8_4=d_hi;
else d8_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(2)==0 || ui(3)==0|| ui(6)==0|| ui(7)==0
    d8_5=d_mi;
else d8_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(2)==0 || ui(3)==0|| ui(6)==0|| ui(7)==0
    d8_6=d_li;
else d8_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(1)==0 || ur(2)==0|| ur(4)==0|| ur(12)==0
    d8_7=d_hr;
else d8_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(1)==0 || ur(2)==0|| ur(4)==0|| ur(12)==0
    d8_8=d_mr;
else d8_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(1)==0 || ur(2)==0|| ur(4)==0|| ur(12)==0
    d8_9=d_lr;
else d8_9=0;
end
D=[d8_1,d8_2,d8_3,d8_4,d8_5,d8_6,d8_7,d8_8,d8_9];
d8=max(D);
t=t+15+d8;
% task 9
uh=rand(1, h) < (1-uhh);
if uh(9)==0
    d9_1=d_hh;
else d9_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(9)==0
    d9_2=d_mh;
else d9_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(9)==0
    d9_3=d_lh;
else d9_3=0;
end
```

```
ui=rand(1,i) < (1-uhi);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(5)==0|| ui(6)==0|| ui(7)==0
    d9_4=d_hi;
else d9_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(5)==0|| ui(6)==0|| ui(7)==0
    d9_5=d_mi;
else d9_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(5)==0|| ui(6)==0|| ui(7)==0
    d9_6=d_li;
else d9_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(3)==0 || ur(5)==0|| ur(6)==0|| ur(7)==0
    d9_7=d_hr;
else d9_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(3)==0 || ur(5)==0|| ur(6)==0|| ur(7)==0
    d9_8=d_mr;
else d9_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(3)==0 || ur(5)==0|| ur(6)==0|| ur(7)==0
    d9_9=d_lr;
else d9_9=0;
end
D=[d9_1,d9_2,d9_3,d9_4,d9_5,d9_6,d9_7,d9_8,d9_9];
d9=max(D);
t=t+10+d9;
% task 10
uh=rand(1, h) < (1-uhh);
if uh(11)==0
    d10_1=d_hh;
else d10_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(11)==0
    d10_2=d_mh;
else d10_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(11)==0
    d10_3=d_lh;
else d10_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(2)==0 || ui(3)==0|| ui(5)==0|| ui(6)==0|| ui(7)==0
    d10_4=d_hi;
else d10_4=0;
end
ui=rand(1,i) < (1-umi);
```

```
if ui(2)==0 || ui(3)==0|| ui(5)==0|| ui(6)==0|| ui(7)==0
    d10_5=d_mi;
else d10_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(2)==0 || ui(3)==0|| ui(5)==0|| ui(6)==0|| ui(7)==0
    d10_6=d_li;
else d10_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(8)==0 || ur(12)==0
    d10_7=d_hr;
else d10_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(8)==0 || ur(12)==0
    d10_8=d_mr;
else d10_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(8)==0 || ur(12)==0
    d10_9=d_lr;
else d10_9=0;
end
D=[d10_1,d10_2,d10_3,d10_4,d10_5,d10_6,d10_7,d10_8,d10_9];
d10=max(D);
t10=t+5+d10;
% task 11
uh=rand(1, h) < (1-uhh);
if uh(12)==0
    d11_1=d_hh;
else d11_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(12)==0
    d11_2=d_mh;
else d11_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(12)==0
    d11_3=d_lh;
else d11_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(6)==0|| ui(7)==0
    d11_4=d_hi;
else d11_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(6)==0|| ui(7)==0
    d11_5=d_mi;
else d11_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(2)==0 || ui(3)==0|| ui(4)==0|| ui(6)==0|| ui(7)==0
```

```
    d11_6=d_li;
else d11_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(9)==0 || ur(10)==0|| ur(12)==0
    d11_7=d_hr;
else d11_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(9)==0 || ur(10)==0|| ur(12)==0
    d11_8=d_mr;
else d11_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(9)==0 || ur(10)==0|| ur(12)==0
    d11_9=d_lr;
else d11_9=0;
end
D=[d11_1,d11_2,d11_3,d11_4,d11_5,d11_6,d11_7,d11_8,d11_9];
d11=max(D);
t11=t+8+d11;
% task 12
uh=rand(1, h) < (1-uhh);
if uh(12)==0
    d12_1=d_hh;
else d12_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(12)==0
    d12_2=d_mh;
else d12_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(12)==0
    d12_3=d_lh;
else d12_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(2)==0 || ui(3)==0|| ui(5)==0|| ui(6)==0|| ui(7)==0
    d12_4=d_hi;
else d12_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(2)==0 || ui(3)==0|| ui(5)==0|| ui(6)==0|| ui(7)==0
    d12_5=d_mi;
else d12_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(2)==0 || ui(3)==0|| ui(5)==0|| ui(6)==0|| ui(7)==0
    d12_6=d_li;
else d12_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(11)==0|| ur(12)==0
    d12_7=d_hr;
```

```
else d12_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(11)==0|| ur(12)==0
    d12_8=d_mr;
else d12_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(11)==0|| ur(12)==0
    d12_9=d_lr;
else d12_9=0;
end
D=[d12_1,d12_2,d12_3,d12_4,d12_5,d12_6,d12_7,d12_8,d12_9];
d12=max(D);
t12=t+12+d12;
MT=[t10,t11,t12];
t=max(MT);
% task 13
uh=rand(1, h) < (1-uhh);
if uh(9)==0
    d13_1=d_hh;
else d13_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(9)==0
    d13_2=d_mh;
else d13_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(9)==0
    d13_3=d_lh;
else d13_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(2)==0 || ui(3)==0|| ui(6)==0|| ui(7)==0
    d13_4=d_hi;
else d13_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(2)==0 || ui(3)==0|| ui(6)==0|| ui(7)==0
    d13_5=d_mi;
else d13_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(2)==0 || ui(3)==0|| ui(6)==0|| ui(7)==0
    d13_6=d_li;
else d13_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(3)==0|| ur(6)==0
    d13_7=d_hr;
else d13_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(3)==0|| ur(6)==0
```

```
    d13_8=d_mr;
else d13_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(3)==0|| ur(6)==0
    d13_9=d_lr;
else d13_9=0;
end
D=[d13_1,d13_2,d13_3,d13_4,d13_5,d13_6,d13_7,d13_8,d13_9];
d13=max(D);
t=t+10+d13;
output(a)=t;
end
```

(5) Code for Monte Carlo Simulation for Vulnerability Assessment of Case Study 3 in Base Scenario

```
for a=1:1000
    AI=[1,1,0,0,0,0,0,0,0,1;
        0,0,1,1,0,1,0,0,0,0;
        0,0,0,1,0,0,0,0,0,0;
        1,0,0,0,1,1,0,1,1,0;
        0,0,0,0,0,0,1,0,0,0;
        0,0,0,0,0,0,1,0,0,0;
        1,0,0,0,0,1,1,1,1,0;
        1,0,0,0,0,1,0,1,1,0;
        0,0,0,0,0,0,0,0,1,0];
     AR=[1,1,1,0,0,0,0,0,0,0,0,0,0,0,0,1,1,1;
         1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,1,1,0,1,1,1,1,1,1,0,1,0,0,0;
         0,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0];
     AT=[1,1,0,0,0,0,0,0,0,0,0,0,0,0,1;
         0,0,1,0,1,0,0,0,0,0,0,0,0,0,0;
         0,0,0,1,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,1,0,0,1,0,1,0,1,0,0;
         0,0,0,0,0,0,1,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,1,0,0,0,0,0,1,0;
         0,0,0,0,0,0,0,1,0,1,0,1,0,1,0;
         0,0,0,0,0,0,0,0,0,1,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,0,1,0,0,0];
     IT=[1,1,0,0,0,0,0,0,1,1,1,0,0,0,0;
         0,1,0,0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,1,0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,1,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,1,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,1,0,0,1,1,1,0,0,0,0;
         0,0,0,0,0,0,1,1,0,0,0,0,0,1,0;
         0,0,0,0,0,0,0,0,1,1,0,0,0,0,0;
         0,0,0,0,0,1,0,0,0,1,1,1,1,0,0;
         0,0,0,0,0,0,0,0,0,0,0,0,0,0,1];
     RT=[1,0,1,0,1,0,0,0,0,0,0,0,0,0,0;
         0,1,0,0,0,0,0,0,0,0,0,0,0,0,0;
         0,1,0,0,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,1,0,0,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,1,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,1,0,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,1,0,0,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,1,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,1,0,0,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,1,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,1,0,0,0,0;
         0,0,0,0,0,0,0,0,0,0,1,0,0,0,0;
```

```
          0,0,0,0,0,0,0,0,0,0,1,0,0,0,0;
          0,0,0,0,0,0,0,0,0,0,0,1,0,0,0;
          0,0,0,0,0,0,0,0,0,0,0,0,1,0,0;
          0,0,0,0,0,0,0,0,0,0,0,0,0,0,1;
          0,0,0,0,0,0,0,0,0,0,0,0,0,0,1;
          0,0,0,0,0,0,0,0,0,0,0,0,0,0,1];
p_h=0.392;
p_i=0.424;
p_r=0.424;
h=size(AT,1);                % number of human agents
uh=rand(1, h) < p_h;         % generate a random vector of human agent
availability based on the level of uncertainty p_h.
r=1;
while r<=h                   % reflect the impact on matrix AI and AR
    if uh(1,r)==1
       AI(r,:)=0;
       AR(r,:)=0;
    end
    r=r+1;
end
i=size(IT,1);                % number of information
ui=rand(1, i) < p_i;         % generate a random vector of information
availability based on the level of uncertainty p_i.
r=1;
while r<=i                   % reflect the impact on matrix AI
    if ui(1,r)==1
       AI(:,r)=0;
    end
    r=r+1;
end
re=size(RT,1);                % number of resources
ur=rand(1, re) < p_r;         % generate a random vector of resource
availability based on the level of uncertainty p_r.
r=1;
while r<=re                   % reflect the impact on matrix AR
    if ur(1,r)==1
       AR(:,r)=0;
    end
    r=r+1;
end
% calculation of number of tasks cannot be implemented due to lack of
% information
supplyinfo=((AT).')*(AI);       % information supply matrix
requireinfo=(IT).';             % information requirement matrix
infogap=supplyinfo-requireinfo; % information gap matrix
n=size(infogap,1);              % number of rows in information gap
matrix
fi=0;                           % original number of failed tasks is 0
r=1;                            % original row number is 1
while r<=n                      % check each row in information gap
matrix
    if any(infogap(r,:)==-1)    % task i fails if any element in row i
is -1
        fi=fi+1;
    end
```

```
    r=r+1;
end
% calculation of number of tasks cannot be implemented due to lack of
% resource
supplyresource=((AT).')*(AR);
requireresource=(RT).';
resourcegap=supplyresource-requireresource;
m=size(resourcegap,1);
fr=0;
r=1;
while r<=m
    if any(resourcegap(r,:)==-1)
        fr=fr+1;
    end
    r=r+1;
end
% calculation of meta-network efficiency
tasknumber=length(AT);
e=((tasknumber-fi)/tasknumber+(tasknumber-fr)/tasknumber)/2;
output(a)=1-e;
end
```

(6) Code for Monte Carlo Simulation for Schedule Deviation Assessment of Case Study 3 in Base Scenario

```
for a=1:1000
d_hh=20; d_mh=10; d_lh=5;      % define human-agent related delay days
d_hr=20; d_mr=10; d_lr=2;     % define resource related delay days
d_hi=20; d_mi=5; d_li=2;      % define information related delay days
h=9;                 % number of human agents
i=10;                 % number of information
r=18;                % number of resources
t=0;                   % initial time
uhh=0.05;            % probability of high-disturbance human disruption
umh=0.2;             % probability of medium-disturbance human disruption
ulh=0.2;             % probability of low-disturbance human disruption
uhr=0.1;            % probability of high-disturbance resource disruption
umr=0.2;          % probability of medium-disturbance resource disruption
ulr=0.2;           % probability of low-disturbance resource disruption
uhi=0.1;            % probability of high-disturbance resource disruption
umi=0.2;          % probability of medium-disturbance resource disruption
uli=0.2;          % probability of low-disturbance resource disruption
% task 1
uh=rand(1, h) < (1-uhh);
if uh(1)==0
    d1_1=d_hh;
else d1_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(1)==0
    d1_2=d_mh;
else d1_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(1)==0
    d1_3=d_lh;
else d1_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0
    d1_4=d_hi;
else d1_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0
    d1_5=d_mi;
else d1_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0
    d1_6=d_li;
else d1_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(1)==0
```

```
    d1_7=d_hr;
else d1_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(1)==0
    d1_8=d_mr;
else d1_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(1)==0
    d1_9=d_lr;
else d1_9=0;
end
D=[d1_1,d1_2,d1_3,d1_4,d1_5,d1_6,d1_7,d1_8,d1_9];
d1=max(D);
t=t+1+d1;
% task 2
uh=rand(1, h) < (1-uhh);
if uh(1)==0
    d2_1=d_hh;
else d2_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(1)==0
    d2_2=d_mh;
else d2_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(1)==0
    d2_3=d_lh;
else d2_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(2)==0
    d2_4=d_hi;
else d2_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(2)==0
    d2_5=d_mi;
else d2_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(2)==0
    d2_6=d_li;
else d2_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(2)==0||ur(3)==0
    d2_7=d_hr;
else d2_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(2)==0||ur(3)==0
    d2_8=d_mr;
```

```
else d2_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(2)==0||ur(3)==0
    d2_9=d_lr;
else d2_9=0;
end
D=[d2_1,d2_2,d2_3,d2_4,d2_5,d2_6,d2_7,d2_8,d2_9];
d2=max(D);
t=t+3+d2;
% task 3
uh=rand(1, h) < (1-uhh);
if uh(2)==0
    d3_1=d_hh;
else d3_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(2)==0
    d3_2=d_mh;
else d3_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(2)==0
    d3_3=d_lh;
else d3_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(3)==0
    d3_4=d_hi;
else d3_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(3)==0
    d3_5=d_mi;
else d3_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(3)==0
    d3_6=d_li;
else d3_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(1)==0
    d3_7=d_hr;
else d3_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(1)==0
    d3_8=d_mr;
else d3_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(1)==0
    d3_9=d_lr;
else d3_9=0;
```

```
end
D=[d3_1,d3_2,d3_3,d3_4,d3_5,d3_6,d3_7,d3_8,d3_9];
d3=max(D);
t=t+1+d3;
% task 4
uh=rand(1, h) < (1-uhh);
if uh(3)==0
    d4_1=d_hh;
else d4_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(3)==0
    d4_2=d_mh;
else d4_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(3)==0
    d4_3=d_lh;
else d4_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(4)==0
    d4_4=d_hi;
else d4_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(4)==0
    d4_5=d_mi;
else d4_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(4)==0
    d4_6=d_li;
else d4_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(4)==0
    d4_7=d_hr;
else d4_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(4)==0
    d4_8=d_mr;
else d4_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(4)==0
    d4_9=d_lr;
else d4_9=0;
end
D=[d4_1,d4_2,d4_3,d4_4,d4_5,d4_6,d4_7,d4_8,d4_9];
d4=max(D);
t=t+4+d4;
% task 5
uh=rand(1, h) < (1-uhh);
```

```
if uh(2)==0
    d5_1=d_hh;
else d5_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(2)==0
    d5_2=d_mh;
else d5_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(2)==0
    d5_3=d_lh;
else d5_3=0;
end
ur=rand(1,r) < (1-uhr);
if ur(1)==0
    d5_7=d_hr;
else d5_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(1)==0
    d5_8=d_mr;
else d5_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(1)==0
    d5_9=d_lr;
else d5_9=0;
end
D=[d5_1,d5_2,d5_3,d5_7,d5_8,d5_9];
d5=max(D);
t=t+1+d5;
% task 6
uh=rand(1, h) < (1-uhh);
if uh(4)==0
    d6_1=d_hh;
else d6_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(4)==0
    d6_2=d_mh;
else d6_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(4)==0
    d6_3=d_lh;
else d6_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(5)==0||ui(6)==0||ui(9)==0
    d6_4=d_hi;
else d6_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(5)==0||ui(6)==0||ui(9)==0
```

```
    d6_5=d_mi;
else d6_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(5)==0||ui(6)==0||ui(9)==0
    d6_6=d_li;
else d6_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(5)==0||ur(6)==0
    d6_7=d_hr;
else d6_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(5)==0||ur(6)==0
    d6_8=d_mr;
else d6_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(5)==0||ur(6)==0
    d6_9=d_lr;
else d6_9=0;
end
D=[d6_1,d6_2,d6_3,d6_4,d6_5,d6_6,d6_7,d6_8,d6_9];
d6=max(D);
t=t+2+d6;
% task 7
uh=rand(1, h) < (1-uhh);
if uh(5)==0
    d7_1=d_hh;
else d7_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(5)==0
    d7_2=d_mh;
else d7_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(5)==0
    d7_3=d_lh;
else d7_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(7)==0
    d7_4=d_hi;
else d7_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(7)==0
    d7_5=d_mi;
else d7_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(7)==0
    d7_6=d_li;
```

```
else d7_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(7)==0
    d7_7=d_hr;
else d7_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(7)==0
    d7_8=d_mr;
else d7_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(7)==0
    d7_9=d_lr;
else d7_9=0;
end
D=[d7_1,d7_2,d7_3,d7_4,d7_5,d7_6,d7_7,d7_8,d7_9];
d7=max(D);
t=t+2+d7;
% task 8
uh=rand(1, h) < (1-uhh);
if uh(6)==0||uh(7)==0
    d8_1=d_hh;
else d8_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(6)==0||uh(7)==0
    d8_2=d_mh;
else d8_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(6)==0||uh(7)==0
    d8_3=d_lh;
else d8_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(7)==0
    d8_4=d_hi;
else d8_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(7)==0
    d8_5=d_mi;
else d8_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(7)==0
    d8_6=d_li;
else d8_6=0;
end
D=[d8_1,d8_2,d8_3,d8_4,d8_5,d8_6];
d8=max(D);
t=t+1+d8;
% task 9
```

```
uh=rand(1, h) < (1-uhh);
if uh(4)==0
    d9_1=d_hh;
else d9_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(4)==0
    d9_2=d_mh;
else d9_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(4)==0
    d9_3=d_lh;
else d9_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(6)==0||ui(8)==0
    d9_4=d_hi;
else d9_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(6)==0||ui(8)==0
    d9_5=d_mi;
else d9_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(6)==0||ui(8)==0
    d9_6=d_li;
else d9_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(8)==0||ur(9)==0
    d9_7=d_hr;
else d9_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(8)==0||ur(9)==0
    d9_8=d_mr;
else d9_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(8)==0||ur(9)==0
    d9_9=d_lr;
else d9_9=0;
end
D=[d9_1,d9_2,d9_3,d9_4,d9_5,d9_6,d9_7,d9_8,d9_9];
d9=max(D);
t=t+4+d9;
% task 10
uh=rand(1, h) < (1-uhh);
if uh(7)==0||uh(8)==0
    d10_1=d_hh;
else d10_1=0;
end
uh=rand(1, h) < (1-umh);
```

```
if uh(7)==0||uh(8)==0
    d10_2=d_mh;
else d10_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(7)==0||uh(8)==0
    d10_3=d_lh;
else d10_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(6)==0||ui(8)==0||ui(9)==0
    d10_4=d_hi;
else d10_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(6)==0||ui(8)==0||ui(9)==0
    d10_5=d_mi;
else d10_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(6)==0||ui(8)==0||ui(9)==0
    d10_6=d_li;
else d10_6=0;
end
D=[d10_1,d10_2,d10_3,d10_4,d10_5,d10_6];
d10=max(D);
t=t+1+d10;
% task 11
uh=rand(1, h) < (1-uhh);
if uh(4)==0
    d11_1=d_hh;
else d11_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(4)==0
    d11_2=d_mh;
else d11_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(4)==0
    d11_3=d_lh;
else d11_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(1)==0||ui(6)==0||ui(9)==0
    d11_4=d_hi;
else d11_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(1)==0||ui(6)==0||ui(9)==0
    d11_5=d_mi;
else d11_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(1)==0||ui(6)==0||ui(9)==0
```

```
    d11_6=d_li;
else d11_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(10)==0||ur(11)==0||ur(12)==0||ur(13)==0
    d11_7=d_hr;
else d11_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(10)==0||ur(11)==0||ur(12)==0||ur(13)==0
    d11_8=d_mr;
else d11_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(10)==0||ur(11)==0||ur(12)==0||ur(13)==0
    d11_9=d_lr;
else d11_9=0;
end
D=[d11_1,d11_2,d11_3,d11_4,d11_5,d11_6,d11_7,d11_8,d11_9];
d11=max(D);
t11=t+1+d11;
% task 12
uh=rand(1, h) < (1-uhh);
if uh(7)==0||uh(9)==0
    d12_1=d_hh;
else d12_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(7)==0||uh(9)==0
    d12_2=d_mh;
else d12_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(7)==0||uh(9)==0
    d12_3=d_lh;
else d12_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(9)==0
    d12_4=d_hi;
else d12_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(9)==0
    d12_5=d_mi;
else d12_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(9)==0
    d12_6=d_li;
else d12_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(14)==0
    d12_7=d_hr;
```

```
else d12_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(14)==0
    d12_8=d_mr;
else d12_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(14)==0
    d12_9=d_lr;
else d12_9=0;
end
D=[d12_1,d12_2,d12_3,d12_4,d12_5,d12_6,d12_7,d12_8,d12_9];
d12=max(D);
t12=t+1+d12;
MT=[t11,t12];
t=max(MT);
% task 13
uh=rand(1, h) < (1-uhh);
if uh(4)==0
    d13_1=d_hh;
else d13_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(4)==0
    d13_2=d_mh;
else d13_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(4)==0
    d13_3=d_lh;
else d13_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(9)==0
    d13_4=d_hi;
else d13_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(9)==0
    d13_5=d_mi;
else d13_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(9)==0
    d13_6=d_li;
else d13_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(15)==0
    d13_7=d_hr;
else d13_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(15)==0
```

```
    d13_8=d_mr;
else d13_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(15)==0
    d13_9=d_lr;
else d13_9=0;
end
D=[d13_1,d13_2,d13_3,d13_4,d13_5,d13_6,d13_7,d13_8,d13_9];
d13=max(D);
t=t+2+d13;
% task 14
uh=rand(1, h) < (1-uhh);
if uh(6)==0||uh(7)==0
    d14_1=d_hh;
else d14_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(6)==0||uh(7)==0
    d14_2=d_mh;
else d14_2=0;
end
uh=rand(1, h) < (1-ulh);
if uh(6)==0||uh(7)==0
    d14_3=d_lh;
else d14_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(7)==0
    d14_4=d_hi;
else d14_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(7)==0
    d14_5=d_mi;
else d14_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(7)==0
    d14_6=d_li;
else d14_6=0;
end
D=[d14_1,d14_2,d14_3,d14_4,d14_5,d14_6];
d14=max(D);
t=t+1+d14;
% task 15
uh=rand(1, h) < (1-uhh);
if uh(1)==0
    d15_1=d_hh;
else d15_1=0;
end
uh=rand(1, h) < (1-umh);
if uh(1)==0
    d15_2=d_mh;
else d15_2=0;
```

```
end
uh=rand(1, h) < (1-ulh);
if uh(1)==0
    d15_3=d_lh;
else d15_3=0;
end
ui=rand(1,i) < (1-uhi);
if ui(10)==0
    d15_4=d_hi;
else d15_4=0;
end
ui=rand(1,i) < (1-umi);
if ui(10)==0
    d15_5=d_mi;
else d15_5=0;
end
ui=rand(1,i) < (1-uli);
if ui(10)==0
    d15_6=d_li;
else d15_6=0;
end
ur=rand(1,r) < (1-uhr);
if ur(16)==0||ur(17)==0||ur(18)==0
    d15_7=d_hr;
else d15_7=0;
end
ur=rand(1,r) < (1-umr);
if ur(16)==0||ur(17)==0||ur(18)==0
    d15_8=d_mr;
else d15_8=0;
end
ur=rand(1,r) < (1-ulr);
if ur(16)==0||ur(17)==0||ur(18)==0
    d15_9=d_lr;
else d15_9=0;
end
D=[d15_1,d15_2,d15_3,d15_4,d15_5,d15_6,d15_7,d15_8,d15_9];
d15=max(D);
t=t+2+d15;
output(a)=t;
end
```

VITA

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