Modeling Construction Competitive Bidding: An Agent-Based Approach

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ABSTRACT

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The construction industry is a complex, multi-level system that includes a large collection of independent, heterogeneous organizations and institutions and is associated with several economic sectors and markets. Because of its unique characteristics, the construction industry as one of the major economic sectors and contributors to the economic development of the nation needs its own specific and dedicated economics. The shortcomings of the existing methodologies call for the use of more sophisticated modeling tools that can capture more important aspects of the real world and its complexity in particular the interconnections among elements of the system, their idiosyncrasies, and emergent behavior. As a pioneer attempt in the exploration of a new theory of construction economics, this study aims to found the first building blocks of the comprehensive economic model of the construction industry. In this dissertation, an agent-based approach is applied to model the low-bid lump-sum construction competitive bidding by which most construction works are allocated. This model has several advantages over the previous analytical and empirical models including the capability of observing the bidding process dynamics, the interaction between the heterogeneous and learning agents, and the emergent bidding patterns arising from multiple scenarios of market conditions and contractors' attributes. Then the model is used as a virtual laboratory for conducting a variety of experiments to answer several important research questions in the field of construction economics. The main research objectives of this study are to: (1) analyze the effectiveness of major quantitative methods in the bidding environment under a variety

of market conditions (2) study the effect of contractors' risk behavior, cost estimating and project management skills, and complexity of projects on contractors' choice of optimal markup, long-term financial growth and market share (3) investigate the impact of risk behavior and need for work on contractors' performance. The results presented in this dissertation offer new understandings and insights on the construction bidding environment and recommendations for both owners and contractors' competitive success, which are not available using conventional approaches. In particular, results suggest that (1) using Friedman model can result in considerably higher market share whereas using Gates model can result in higher profit per project, (2) the optimal policy for contractors is moderation in both dimensions of risk attitude and need for work, (3) the comparative performance of slightly and extremely risk averse contractors are depending on level of cost estimating accuracy and project execution skills of contractors as well as the level of project complexities.

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CHAPTER 1. INTRODUCTION

"As far as the laws of mathematics refer to reality, they are not certain; and as far as they are certain, they do not refer to reality." ~ Albert Einstein

1.1. Overview

The construction industry as one of the major economic sectors in any economy plays a significant role in the economic development. The construction industry can be best understood and analyzed as system-of-systems, a complex, multi-level system that includes a large collection of independent, heterogeneous organizations and institutions and is associated economic sectors and markets. While there are numerous modeling techniques available in the field of economics construction needs its own specific and dedicated economics because of several reasons including but not limited to the facts that: (1) the size of the industry is considerable and its contribution to the whole economy, employment, welfare, and development of other industries is significant; (2) the final product of the construction process is large, immobile, capital-intensive, and often unique; (3) construction markets are very diverse and fragmented; (4) demand for construction services and products is highly interdependent with the current and future state of the economy; and (5) mechanism for price determination is highly complex.

Construction bidding environment is an important component of the industry since allocation of contracts and consequently the price of construction services are usually determined through some form of competitive bidding (Myers, 2013). Competitive bidding is a mechanism universally used by construction clients to allocate construction work to contractors and also establish the market price (D. S. Drew, 2010). Construction bidding is a challenging and risky process where competing contractors of different types and sizes with various short-term and long-term goals and strategies, seek to win the offered project at the best value. There are a number of bidding methods (including the lowest bid, the average bid, the second lowest bid, and the best value bid) and selection criteria (including price, time, and quality) that are utilized by owners to choose the best contractor and ensure the project is delivered in accordance with its objectives (Gordon, 1994). Although construction bidding may be similar to auctions of manufactured products, airport slots and online advertisements (as known as AdWords) in terms of rules and procedures, its dynamics vary in many ways due to the nature and complexities of construction works (Runeson & Skitmore, 1999).

1.2. Problem Statement

The construction bidding environment is a perfect example of an interactive, dynamic and complex system of heterogeneous and autonomous agents (contractors and owners). Complexity of the construction bidding environment originates from a large number of actors with uncertain, heterogeneous but interdependent behavior interacting with themselves and construction projects. Researchers have investigated different aspects of construction bidding from both contractors' and owners' perspectives using analytical and empirical approaches. Accordingly, the literature can be divided into two main categories: (1) statistical models that have been applied to model and predict behavior of the market or price fluctuations, and (2) mathematical and game theoretic models that are built that on strong assumptions such as rational agents and linearity. These two categories of models usually fail to capture complexity and dynamics of bidding environment by disregarding interactions among players. Due to the methodological restrictions and limited applicability of previous research studies to address existing research questions, there is a need for developing a proper methodology that captures complexity of the construction bidding environment.

1.3. Research Objectives

The primary goal of this study is to develop an agent-based model of the construction bidding environment and utilize it as a virtual laboratory to conduct a variety of simulation experiments to answer the following research questions:

- What is the impact of the choice of learning mechanisms on contractors' financial performance, success rate, and market share under a variety of market scenarios?
- How do these learning mechanisms perform in competition against each other and irrational players?
- How does the interaction among risk attitude, cost estimating accuracy and project management skills impact contractors' performance in low and high risk markets?
- Is there an optimal level of risk attitude by which contractors can improve their long-term performance?
- Should a markup discount be considered to account for need for work? If yes, to what degree?

1.4. Research Significance

Understanding of the construction industry as a system-of-systems can lead the way for further research in this discipline. This dissertation, as a part of this ambitious project, is an attempt to create the first fundamental building blocks of this economic model of the construction industry. Specifically, this dissertation focuses on modeling and analyzing the most prevailing form of market in the construction industry, the competitive bidding environment. The main research development of this study contribute to the advancement of current theory and practice of construction bidding. The developed virtual laboratory can serve as an experimental tool that can be used by any potential user (owner or contractor) to evaluate and compare different bidding strategies and project tendering approaches. It can also serve as an educational tool in academic forums and classes to teach construction management students.

1.5. Research Methodology

The complexity of the construction bidding environment can be captured only through a bottom-up modeling approach that focuses on the interactions among the components of the system. Agent based modeling (ABM) is used to develop the simulation model. ABM provides a platform in which contributions of the previous studies can be used for defining and building elements of the model such as project attributes and contractors' possible goals and behaviors as well as establishing relationships amongst those elements. To understand and analyze the construction bidding dynamics, ABM offers several advantages over other modeling and simulation methods:

- ABM takes into account the bounded rationality and learning capability of agents. As opposed to mathematical and game theoretic modeling.
- ABM allows consideration of heterogeneous agents that have different goals, behaviors and capabilities.
- ABM provides modelers with the ability to conduct experiments under various scenarios with little effort.
- ABM can be used for performing ex-ante analysis of complex systems. Dynamic game theoretic analysis uses backward induction.
- ABM has shown great potential in dealing with emergent behaviors of complex systems.

1.6. Thesis Organization

The organization of this dissertation and its relation to the main research tasks are shown in Table 1.1.

Table 1.1. Organization of the dissertation and list of tasks in order to accomplish the dissertation objectives

Organization	Task #	Task Description
Chapter 1		Introduction to the dissertation
Chapter 2	1	Overview of key concepts in the field of construction economics, agent-based modeling, and system-of-systems in order to form a solid point of departure for the present study
Chapter 3	2	A comprehensive review and categorization of scientific studies in the field of competitive construction bidding based on the methodological approach
	3	Identification of the need and proper methodology for developing a comprehensive model that captures the dynamics of bidding environment
	4	Development of an agent-based model of the construction competitive bidding environment
Chapter 4	5	A review of major quantitative bidding models are identified in the literature
	6	Implementation of the selected quantitative bidding methods in the model
	7	Design and conduct of experiments for comparing of the effectiveness of these methods in the bidding environment under a variety of scenarios
Chapter 5	8	An extensive review of the literature to identify the key parameters involved in the bidding process
	9	Formulation and implementation of the complex interaction among contractors' risk behavior, cost estimating and project management skills, and complexity of projects
	10	Design and conduct of experiments for analyzing the impact of risk attitude, cost estimating accuracy, project management skills, and project complexity on contractors' performance and the market
Chapter 6	11	An extensive review of descriptive studies in the literature to build a rule-based markup decision model that replicates behavior of a typical contractor
	12	Formulation and implementation of the multi-criteria bidding methods in the model
	13	Design and conduct of experiments for studying impact of consideration of risk allowance and need for work on contractor's financial success in a long run
Chapter 7	14	Verification of the agent-based models
	15	Validation of the agent-based models
Chapter 8	16	Conclusions
	17	Recommended future works

CHAPTER 2. LITERATURE REVIEW

"No science thrives in the atmosphere of direct practical aim. We should still be without most of the conveniences of modern life if physicists had been as eager for immediate applications as most economists are and always have been." J. Schumpeter

2.1. Introduction

This chapter aims to overview key concepts in the field of construction economics and system-of-systems. This provides the foundation for understanding the main purpose of the dissertation, the methodology used in the dissertation, and the reason for this choice. The first section provides a brief overview on the construction industry. The "Construction Economics" section elaborates on the need for developing an economic understanding of the industry with respects to its unique characteristics. Then, agent-based modeling (ABM) is introduced as an advanced methodology used for economic modeling of complex systems and compared against other methodologies. In the next section, system-of-systems is introduced and recommended to facilitate applying any methodology to an economic or managerial problem in construction. System-of-systems serves as a lens to look at the industry so that the problem can be best defined, abstracted, and modeled using a variety of methodologies.

2.2. Construction Industry: Overview

The construction industry is a complex, multi-level system that includes a large collection of independent, heterogeneous organizations and institutions and is associated economic sectors and markets including but not limited to public clients, private developers, financiers, contractors, architects, designers, consultants, suppliers, manufacturers, subcontractors, facility managers, professionals societies, regulatory agencies, and labor unions. As shown in Figure 2.1, the constituents of this system are interconnected with each other at different levels as well as other sectors and industries in the economy at local, regional, national, and global levels.

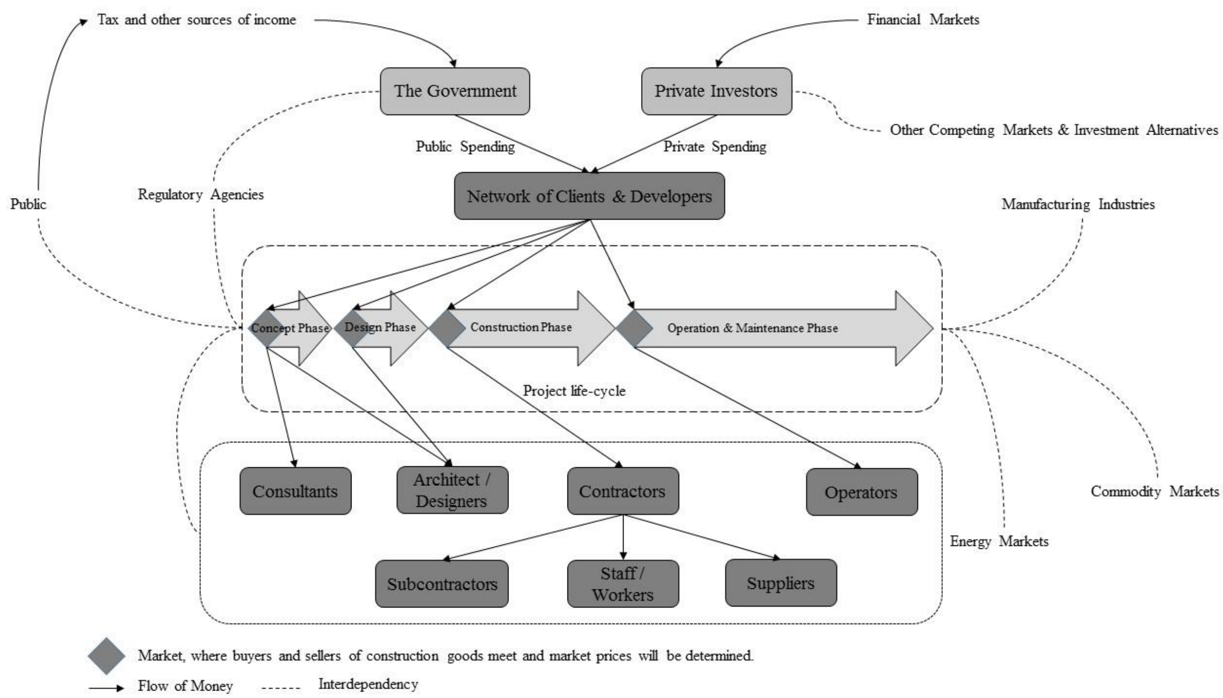


Figure 2.1. A schematic representation of the construction industry as a complex, multi-level system

The construction industry as one of the major economic sectors in any economy plays a significant role in the economic development. According to a Price-Waterhouse-Coopers (PwC)-sponsored report, the construction industry accounted for more than 11 percent of the global GDP in 2011 and this share is projected to reach 13.2 percent by 2020 (Roumeliotis, 2011). The total value of public investment in construction will increase to $14.5 trillion in the U.S. by 2020, with growth averaging 7.8 percent per year over the next five years (Roumeliotis, 2011). Although, this investment in most developed countries is constrained due to large public deficits, austerity programs, slow population growth and limited economic expansion, the United States will be the exception given its growing population. Besides its significant role in the whole economy, the construction industry has also many extensive linkages with other industries. For example, residential building is among the most labor-intensive activities; the construction industry has critical recruitment, training, skills and safety issues; and, acquisition of a house is almost considered as the largest investment most individuals can make (De Valence, 2010). Despite the important role in the economy and the interdependency with other industries, to my best knowledge most of the published research studies in construction related journals and conferences have concentrated on different aspects of construction projects and project management. Construction has been and will always be a project-based industry. However, modeling and analyzing projects and the dynamics among involved parties at project level is necessary but not enough to develop an understanding of the industry. There is a need to develop a comprehensive economic model of the industry using a systematic approach. This model can consider strategic behavior of firms, various forms of project delivery and contractor selection (known as allocation mechanism in economics), market structure, public policies, regulatory measures, and linkages with other industries through supply chains of materials, money, services, and labors.

2.3. Construction Economics: Definition and Domain

There is still lack of a consensus on definition, domain, and content of construction economics. However, the two most prevalent views on construction economics are:

1. Construction economics is the application of economics to the study of the construction firm, the construction process, and the construction industry (Cooke, 1996; Hillebrandt, 2000; Raftery, 1991).

2. Construction economics is concerned with the allocation of scarce resources (Gruneberg, 1997; Myers, 2013; Ofori, 1990; Robbins, 2007).

Construction economics has not yet developed to the point where it could be acknowledged as a distinct branch of general economics (Ofori, 1994). However, many scholars in both the academia and the industry argue that construction needs its own specific and dedicated economics because of several reasons including but not limited to the following (De Valence, 2010):

- The size of the industry is considerable and its contribution to the whole economy, employment, welfare, and development of other industries is significant.
- The final product of the construction process has unique characteristics; it is large, immobile, capital-intensive, and often one-off.
- Construction markets are very diverse and fragmented; a large number of small geographically dispersed firms with diverse specialties dominate the industry. According to the US bureau of labor statistics about 80% of construction payroll establishments had 1 to 9 employees.
- Demand for construction services and products is highly dependent on the current and future state of the economy.
- Mechanism for price determination is highly complex. The price of the final product is usually determined through a number of tendering processes.
- The construction industry tends to be stable over the long term, while it is also remarkably unstable in the short term, in particular during periods of economic adjustment. The construction industry contracts earlier and more quickly than the whole economy when the economy contracts. On the other hand, despite its faster growth at the time of recovery, the

construction industry starts its recovery later than the economy. Construction works are very seasonal; most layoffs in the industry occur in the fourth quarter of each year.

Consistent with the classic categorizations of economics, construction economics can be divided into three main branches: construction microeconomics, construction macroeconomics, and construction mesoeconomics. Table 2.1 presents definition and associated topics of each branch of construction economics.

Table 2.1. Definition and topics of the three branches of construction economics

Field	Definition	Topics
Construction Microeconomics	It studies the behavior of involved individuals and organizations through lifecycle of projects at different levels in making decisions on the allocation of their limited resources.	Market analysis; Competitive bidding; Project delivery systems; Project evaluations; Cost analysis and management; Decision under uncertainty; Construction labor economics.
Construction Mesoeconomics	It is an intermediate level between microeconomics and macroeconomics, dealing with the economies of the entire sector and focuses on the structure of the industry and interdependencies among constituents of the industry.	A holistic approach towards the industry; Industrial organization; Complexity.
Construction Macroeconomics	It focuses on the performance of the industry as a whole. It studies aggregated indicators of the construction industry such as construction spending and price indexes to understand how the whole economy functions.	Construction output; Aggregate demand and supply of construction services; Construction unemployment; Inflation and deflation of prices; Global construction market.

Through life cycle of a project, there can be a number of markets: a market for architecture and design services, a market for construction, and a market for operation and maintenance (See Figure 2.1). Each market has its own specific allocation mechanism. In construction markets, buyers (usually public and private clients) and sellers (usually contractors) meet to agree on a price and a quantity for construction goods. Therefore, the term “market” has a narrower meaning than the term “industry” which can be defined as a branch of trade. Construction goods be they tangible (structures) or intangible (services) have a special feature; they can be characterized as contract goods (not as exchange goods). This is because when the contract is signed, the contractor agrees to produce and deliver the good without deficiencies as specified in the contract and the client agrees to pay right away. On the other hand, exchange goods are produced before procurement (Brockmann, 2010). Contractors compete for construction contracts through one of these three ways: (1) direct negotiation (2), competition, or (3) competition followed by negotiation (D. S. Drew, 2010). Thus, the construction market can take on any structure, from perfect competition through imperfect competition (monopolistic competition and oligopoly) and up to monopoly (De Valence, 2010).

2.4. Conventional Economic Modeling Approaches

Economic models as simplified representations of the real world are being developed to understand, explain and predict economic phenomenon (Myers, 2013). Modeling a market, an industry or the whole economy is of particular interest for policy makers due to the need to evaluate the impact of the envisaged policies on the system as well as for players involved to adopt the best strategy for achieving their goals. In economics, the two most prevalent, yet flawed, decision-making tools for economic policy analysis are (Farmer & Foley, 2009):

1. Econometrics or empirical statistical models,
2. Dynamic stochastic general equilibrium / Game theoretic models.

Statistical models use past data to predict future. They are valuable as long as the world in the future is similar to the world in the past and the relationship between the past and the present is constant. On the other hand, dynamic stochastic general equilibrium and game theoretic models are built on strong assumptions such as rational agents and linearity that make the model unrealistic (Farmer & Foley, 2009). These two categories of models usually fail to capture complexity and interaction of the interconnected system constituents and are not reliable at times of radical change and crisis. One example is their failure to predict the financial crisis in 2008 (Buchanan, 2009) when a major change in one market had ripple effects on other related markets and the whole economy. These shortcomings of the conventional models call for the use of more sophisticated modeling tools that can capture more important aspects of the real world and its complexity in particular the interconnections among elements of the system, their idiosyncrasies, and emergent behavior. Complexity of the construction industry originates from a large number of actors with uncertain, heterogeneous but interdependent behavior interacting with themselves and other actors from other industries. Complexity at levels of project, firm, market, and the industry has been conceptualized and discussed in the literature (Baccarini, 1996; Bertelsen, 2003a, 2003b; Dubois & Gadde, 2002; Gidado, 1996; Wood & Gidado, 2008). However, a proper methodology to model complexity and systematic approach to its implementation for the construction industry have not been proposed yet.

2.5. Agent-Based Modeling: A New Economic Modeling Approach

Thanks to the advances in the field of computer science in particular object-oriented programming, a movement has been formed in economics with the aim of developing a new economic thinking and modeling. This resulted in the creation of agent-based computational economics, which is an attempt to explore the intersection of management science, evolutionary economics, and computer science.

Agent-Based Modeling (ABM), as one of the central modeling and simulation tools in the field of computational economics, can offer solutions for the challenges that the conventional methods have not been able to overcome. Increasing tendency to apply ABM is not only due to the developments in computer modeling and simulation techniques and increased computer capabilities but also because of a paradigm shift in understanding economic phenomenon. The main premise of ABM is that a system should be viewed as a group of components interacting with each other in a dynamic web of relationships and not just as the sum of its parts. With regard to this way of economic thinking, markets can be viewed as inherently dynamic rather than static systems.

In ABM, the agents are computational objects interacting according to rules over space and time. They can represent individuals, organizations, biological entities, and/or physical systems. The rules are defined to model behaviors and social interactions based on incentives and information (Page, 2005). Agents can be designed to learn from other agents and the environment and to adapt to new situations. This evolutionary adaptation in one agent affects the evolution of another agent (known as coevolution in a system). ABM allows the modeler to make more realistic assumptions while the conventional approaches use mathematical proofs to model its theories. The conventional approaches usually fail to explain innovation and growth except as the result of random exogenous shocks from technology. According to (Tesfatsion, 2006), the ultimate scientific objective of ABM is to "*test theoretical findings against real-world data in ways that permit empirically supported theories to cumulate over time, with each researcher's work building appropriately on the work that has gone before*".

An agent-based model contains the following three ingredients (Windrum, Fagiolo, & Moneta, 2007):

1. Bottom-up perspective: The properties of macro-dynamics of a system can be best understood as the outcome of micro-dynamics involving constituent entities (Tesfatsion, 2002).
2. Boundedly-rational agents: Agents should be assumed to behave as boundedly rational entities with adaptive expectations rather than hyper-rational entities with rational expectations.
3. Networked direct interactions: Agents have direct interactions with each other since through adaptive expectations their current decisions directly depend on the past decisions and actions made by other agents in the environment.

Due to its holistic approach and capability to deal with complex systems, ABM can be utilized for various research purposes including but not limited to prediction, proof, discovery, education and training (R. Axelrod, 1997). ABM has recently received a considerable amount of attention from researchers in several domains of social sciences, economics and engineering, and therefore its applications have largely increased over the last two decades. In particular, it has been extensively applied for modeling and analyzing competitive, interactive environments, and markets in several industries such as:

- financial markets (S.-H. Chen & Yeh, 2001; Farmer et al., 2012; Howitt & Clower, 2000; Izumi & Ueda, 1998, 2001; LeBaron, 2000, 2001; X. Liu, Yang, & Tang, 2007; Palmer, Arthur, Holland, & LeBaron, 1999; Tay & Linn, 2001; H. Zhou, Jiang, & Zeng, 2010),
- electricity markets (Bower & Bunn, 2001; Bunn & Oliveira, 2001; Fekete, Nikolovski, Puzak, Slipac, & Keko, 2008; Knežević, Fekete, & Nikolovski, 2010; Nicolaisen, Petrov, & Tesfatsion, 2001; Weidlich & Veit, 2008; Z. Zhou, Wang, & Botterud, 2011; Z. Zhou, Zhao, & Wang, 2011),

- trade networks of buyers and sellers (Albin & Foley, 1992; Kirman, 1997; Tesfatsion, 1997a, 1997b; Vriend, 1995; Weisbuch, Kirman, & Herreiner, 1997, 2000; Wilhite, 2001),
- labor networks (Neugart, 2008; Nicolaisen et al., 2001; Tassier & Menczer, 2001; Tesfatsion, 1998),
- housing markets (Geanakoplos et al., 2012; Magliocca, Safirova, McConnell, & Walls, 2011; Meen & Meen, 2003),
- urban land markets (Filatova, Parker, & Van der Veen, 2009), and
- online auctions (Mizuta & Steiglitz, 2000).

A prime example of ABM application in large-scale is the Eurace@Unibi model, which has been under development since 2006 with the aim of building a comprehensive model of the European economy with integrating goods markets, labor markets, financial markets, and credit markets (Silvano Cincotti, Raberto, & Teglio, 2010; S Cincotti, Raberto, & Teglio, 2012; Dawid, Gemkow, Harting, Van der Hoog, & Neugart, 2012; Deissenberg, Van Der Hoog, & Dawid, 2008; Teglio, Raberto, & Cincotti, 2010).

As for bidding in the construction industry, an evolutionary Monte-Carlo simulation model was developed to examine the effects of risk attitude on a contractor's success and on the market structure (Kim & Reinschmidt, 2010). While this model considers contractors as individual agents competing with each other in a market, learning capability of contractors from each other and the environment has been ignored. Because the model does not cover the three ingredients mentioned above, it can hardly be considered as a true application of agent-based modeling. However, in civil engineering domain, ABM has been employed for various purposes such as infrastructure management (Bernhardt & McNeil, 2008), analysis of financial innovation policies (Mostafavi, Abraham, & DeLaurentis, 2013), subcontractor selection (Unsal & Taylor, 2010), dispute resolution (El-Adaway & Kandil, 2009) and sustainable design and management of the built environment (Azar & Menassa, 2011, 2013; J. Chen, Jain, & Taylor, 2013; Said et al., 2013).

2.6. System-of-Systems

There is still no consensus about the definition of system-of-systems (SoS). The term system-of-systems became more common and used in the literature after the seminal works of (Berry, 1964) and (Ackoff, 1971). There are at least sixteen different definitions in the literature for SoS (Lane & Valerdi, 2007). Each definition suggests several characteristics that differentiate systems-of-systems from legacy systems (Boardman & Sauser, 2006; Carlock & Fenton, 2001; Daniel DeLaurentis, 2005a; Jamshidi, 2008; Kotov, 1997; Lewis et al., 2008; Maier, 1996; Manthorpe, 1996; Sage & Cuppan, 2001). The most referenced traits of the constituents of a SoS are:

- Interoperability
- Operational independence
- Managerial independence
- Heterogeneity
- Evolving nature
- Emergence

Transportation systems, the Internet, integrated air defense networks, and enterprise information networks are examples of systems that match the system-of-systems traits (Haskins & Forsberg, 2011; Maier, 1996).

The system-of-systems approach for decomposing complex systems has been applied in several domains including but not limited to transportation systems (Datu B Agusdinata, Fry, & Delaurentis, 2011; Daniel DeLaurentis, 2005b; E. Han & DeLaurentis, 2006; M. Han, Fan, & Guo, 2005; J.-H. Lewe & DeLaurentis, 2004; J. Lewe, DeLaurentis, & Mavris, 2004; Mansouri, Gorod, Wakeman, & Sauser, 2010; Mansouri, Gorod, Wakeman, & Sauser, 2009), emergency management (S. Liu, 2011), policy making for civil infrastructure systems (Mostafavi, Abraham, & Lee, 2012), policy making for the energy sector (Datu Buyung Agusdinata & DeLaurentis, 2008), electrical systems (Pruyt & Thissen, 2007), medical imaging systems (Chandrashekar, Gautam, Srinivas, & Vijayananda, 2007), telecommunication systems (Noam, 1994), healthcare systems (P.-C. DeLaurentis & DeLaurentis, 2010; Grigoroudis & Phillis, 2013; Rusu, Taggart, Desmond, & Lopez, 2013; Wickramasinghe, Chalasani, Boppana, & Madni, 2007; Wickramasinghe, Chalasani, & Koritala, 2012), and financial markets (Kilicay-Ergin & Dagli, 2008; Osmundson, Langford, & Huynh, 2009). Review of the literature indicates that the system-of-systems approach has not been utilized to develop macroeconomic and microeconomic models for complex systems with economic functions.

With identifying its characteristics as a complex system in the former sections of this chapter and mapping them with the generic traits of system-of-systems, the construction industry can be best perceived and analyzed as a system-of-systems and not as a legacy monolithic system. The construction industry demonstrated all the standard traits of a system-of-systems. Its components are heterogeneous, operationally independent, and managerially independent while they are working together. Its markets have shown evolving nature (Kim & Reinschmidt, 2011) and emergent behaviors such as the hold-up problem (Unsal & Taylor, 2010) that cannot be captured analytically.

2.7. Connecting the Dots: Where this Dissertation Locates

The complete modeling of the construction industry and its relationship with the economy will require the analysis of a large number of intersystem interdependencies. This needs to be achieved whilst adopting a holistic approach that does not neglect the fact that the whole of the system is more than its parts. Modeling the actors, components, economic environment, interactions, and complexity of the construction industry as a system-of-systems will advance the understanding of the overall economic behavior of the industry and the emergent behavior of its components. Since ABM is a bottom-up approach that derives the aggregate behavior of a system from micro-level interactions, it is an effective modeling tool for the implementation phase of the system-of-systems approach. This approach presents the required steps for the development of a high-fidelity economic model that replicates the economic behavior of the construction industry in the United States. This research study has unique academic and practical contributions. It advances the knowledge in the field and provides the US policy-makers with a decision support tool that has never existed. This dissertation, as a part of this ambitious study, is an attempt to create the first fundamental building blocks of this economic model of the construction industry. Specifically, this dissertation focuses on modeling and analyzing the most prevailing form of market in the construction industry, the competitive bidding environment.

Understanding of the construction industry as a system-of-systems can lead the way for further research in this discipline. In order to achieve this objective, an understanding of the theoretic aspects of the construction industry as related to its composition and the characteristics of its components is required. Construction bidding environment is an important component of the industry. The next chapter is dedicated to the development of an agent-based model (ABM) of construction bidding environment.

CHAPTER 3. DEVELOPMENT OF A VIRTUAL LABORATORY FOR ANALYSIS OF CONSTRUCTION COMPETITIVE BIDDING

"A 'system' can be defined as a complex of elements standing in interaction. There are general principles holding for systems, irrespective of the nature of the component elements and the relations of forces between them. ...In modern science, dynamic interaction is the basic problem in all fields, and its general principles will have to be formulated in General Systems Theory." ~ Ludwig von Bertalanffy, Problems of Life

3.1. Introduction

In the construction industry, allocation of contracts and consequently the price of construction services are usually determined through some form of competitive bidding (Myers, 2013). Competitive bidding is a mechanism universally used by construction clients to allocate construction work to contractors and also establish the market price (D. S. Drew, 2010). Variations, such as negotiated contracts (cost-plus contract), comprise merely a small portion of the market because majority of the clients are more willing (and/or sometimes obliged in the case of public owners) to deliver their project through competition (Harris & McCaffer, 2013). It is worth mentioning that the two main categories of competitive bidding contracts are the lump-sum contract and the unit-price contract.

Construction bidding is a challenging and risky process where competing contractors of different types and sizes with various short-term and long-term goals and strategies, seek to win the offered project at the best value. There are a number of bidding methods (including the lowest bid, the average bid, the second lowest bid, and the best value bid) and selection criteria (including price, time, and quality) that are utilized by owners to choose the best contractor and ensure the project is delivered in accordance with its objectives (Gordon, 1994). Although construction bidding may be similar to auctions of manufactured products, airport slots and online advertisements (as known as AdWords) in terms of rules and procedures, its dynamics vary in many ways due to the nature and complexities of construction works (Runeson & Skitmore, 1999). Despite the involved risks and the limited available information, contractors have to make a number of simultaneous and interdependent decisions in a timely manner. They have to quote a price before the project starts when all the costs are not yet known. Therefore, the auction theory may not help analyze the construction bidding given that the private value is uncertain for the bidder (M. Skitmore, Runeson, & Chang, 2006). For owners, there is always uncertainty about whether or not the currently employed contractor selection method is optimal, can lead to a successful project, and can generate best value in the long run (Holt, 1998). Therefore, understanding the bidding environment is of significance for both sides of the construction market: owners as demanders and contractors as suppliers.

Researchers have investigated different aspects of construction bidding from both contractors' and owners' perspectives using analytical and empirical approaches. Due to methodological restrictions and limited applicability of previous research studies, there is a need for developing a comprehensive model that helps understand the dynamics of bidding environment by considering interactions among players. In this chapter, agent based modeling (ABM) is used to develop such a model. ABM provides a platform in which contributions of the previous studies can be used for defining and building elements of the model such as project attributes and contractors' possible goals and behaviors as well as establishing relationships amongst those elements. This chapter is organized as follows: The “Construction Bidding Literature” section extensively reviews the literature on construction bidding by taking a new approach to categorize the previous studies. It also discusses their shortcomings compared to the applied methodology which is agent-based modeling. Next, the “Methodology” section describes the development of an agent-based model of construction bidding environment using a system-of-systems analysis approach that includes three phases of definition, abstraction, and implementation. Finally, the developed model in this chapter will be used for different experiments in next chapters in order to first verify the model and then investigate the proposed research questions in this thesis.

3.2. Literature Review on Construction Bidding

Based on the applied research methodologies, the literature of construction bidding can be classified into three main broad categories:

- Deduction: the deriving of a conclusion by reasoning,
- Induction: inference of a generalized conclusion from particular instances, and
- Simulation: the imitative representation of the functioning of one system or process by means of another.

3.2.1. Deduction

A scientific inquiry based on deduction involves specifying a set of assumptions and reaching certain conclusions and theories in a logical and consecutive process (R. Axelrod, 1997). Under this category, several models (Ahmad & Minkarah, 1987; Carr, 1982; Friedman, 1956; Gates, 1967; King & Mercer, 1990; Morin & Clough, 1969; Park & Chapin, 1992; Wade & Harris, 1976) were proposed for optimal markup strategy, assuming that all contractors are seeking to maximize their expected profit while considering opponents’ bid history. Later, the assumption of maximizing the expected monetary value as an objective function was replaced with its expected utility in order to incorporate the risk attitudes of contractors (Ibbs & Crandall, 1982; Willenbrock, 1973). Moreover, other possible determinant factors such as loss avoidance and work force continuity were taken into consideration for developing multi-attribute models of bidding strategy, more realistically reflecting contractors' behaviors (Cagno, Caron, & Perego, 2001; Dozzi, AbouRizk, & Schroeder, 1996; Marzouk & Moselhi, 2003; Seydel & Olson, 1990; Shen, Drew, & Zhang, 1999; M. Skitmore & Pemberton, 1994; Wang, Dzeng, & Lu, 2007). In order to develop appropriate bid compensation strategies for owners, game theory, that is based on rational choice paradigm, was applied to understand the impacts of bid compensation in projects with high bid preparation cost (Ho & Hsu, 2013; Ping Ho, 2005). It is noteworthy to mention that the developed decision models under this category are mostly prescriptive rather than descriptive, i.e., they provide prescriptions on *'how a decision should be made rather than describing how decision is made'* (Bazerman & Moore, 2012) .

3.2.2. Induction

On the other hand, induction starts with specific observations, conducting surveys, and gathering empirical data. Through discovering patterns and regularities in the data, some tentative hypotheses are formulated for further investigation and finally some general conclusions or theories are developed (R. Axelrod, 1997). Under this category, there is a series of studies that conducted questionnaire surveys and interviews in order to reveal the underlying factors that characterize the bidding decision-making process and contractor selection methods (Ahmad, 1990; Ahmad & Minkarah, 1988; Chua & Li, 2000; Dulaimi & Shan, 2002; Egemen & Mohamed, 2007; El-Mashaleh, 2012; S. H. Han & Diekmann, 2001; Hatush & Skitmore, 1997; Shash, 1993; Ye, Li, & Shen, 2012; Ye, Shen, Xia, & Li, 2014). Furthermore, artificial intelligence (Art

Chaovalitwongse, Wang, Williams, & Chaovalitwongse, 2011; Chao, 2007; Chua, Li, & Chan, 2001; Fayek, 1998; M. Han et al., 2005; Hegazy & Moselhi, 1994; Heng Li & Love, 1999; H Li, Shen, & Love, 1999; M. Liu & Ling, 2003, 2005) and statistical analysis (Carr & Sandahl, 1978; D. Drew & Skitmore, 1997; Ngai, Drew, Lo, & Skitmore, 2002; M. Skitmore, 1991) were employed to use past data and develop bidding models to help contractors with the decisions of bid/no bid and optimal markup.

3.2.3. Simulation

While most previous research attempts took either inductive or deductive approaches, simulation has also received some attention in the construction bidding literature. According to (R. Axelrod, 1997), simulation is the third way of conducting scientific research especially in social sciences. A research based on simulation begins with specifying a set of assumptions, similar to a deductive approach, and then analyzes the generated data using an inductive approach (R. Axelrod, 1997; R. M. Axelrod, 1997). Simulation provides researchers with appropriate tools for designing and running a wide range of controlled experiments.

There are a number of simulation techniques that have been developed. Each one has its own strengths and limitations. In construction bidding literature, "live simulation" has been utilized to benefit from the industry practitioners' and experts' knowledge and experience to uncover possible behaviors and decisions of contractors in different situations. In one study, (de Neufville & King, 1991) devised a bid simulation exercise to obtain valid utility functions for construction contractors. After conducting a statistical analysis, they concluded that the need for work and risk have substantial impact on contractors' bid markups. In another study, involving experienced respondents in 60 simulated bidding games, (D. S. Drew & Skitmore, 2006) refuted Vickrey's revenue equivalence principle (Krishna, 2010; Vickrey, 1961). They showed that in construction bidding context, the amount that an owner has to pay the winning contractor in the long run will not be the same in the case of using second price auction instead of the conventional first price auction. In a series of studies involving managers of medium to large contractors from Hong Kong and Singapore, decision to bid and markup behaviors of contractors in different market conditions and firm situations were statistically analyzed using the data gathered from bidding experiments (Lan Oo, Lo, & Teck-Heng Lim, 2012; Oo, Drew, & Lo, 2008a, 2008b, 2010). Finally, (Unsal & Taylor, 2011) empirically examined the existence of hold-up problem in subcontracting process using an internet-based interactive bidding simulation. While live simulation appears promising, the need for having real people (often experienced experts) playing the role of individual decision makers, pressure on researchers for assuring that there are no mistakes in the experimental process, and limited time and resource for running a large enough number of experiments make it impractical in many cases.

As explained in chapter 2, ABM has been recognized as a powerful tool for modeling and simulating the behaviors and interactions of autonomous agents with the intention of assessing their impacts on the system. To understand and analyze the construction bidding dynamics, ABM offers several advantages over other modeling and simulation methods:

- ABM takes into account the bounded rationality and learning capability of agents. As opposed to game theoretic modeling, agents in ABM can adopt complex and adaptive strategies such as “exploration and exploitation” (Cyert & March, 1963; March, 1991; Valluri, North, & Macal, 2009) by learning from the environment and other agents. While game theory has been recognized as a powerful tool for modeling and analyzing conflict and cooperation between intelligent rational decision makers (Neumann & Morgenstern 1947), its strong assumptions and inflexible structure make it less applicable to construction problems. In order to analyze and solve a game (in particular a dynamic game which is more relevant to real interactions in construction than a static game), end outcomes of the game is needed to be known. A comprehensive review of game theory applications in construction management can be found in (Asgari, Afshar, & Madani, 2013).

- ABM allows consideration of heterogeneous agents that have different goals, behaviors and capabilities. This is of special importance due to the heterogeneity of construction market players.

- The ability of integrating contributions of the previous studies makes an ABM approach sufficiently robust and of great value for developing a virtual laboratory. Agent-based computational laboratory of financial markets (Farmer et al., 2012), housing markets (Geanakoplos et al., 2012; Magliocca et al., 2011), electricity markets (North et al., 2002) and the global energy system (Voudouris, Stasinopoulos, Rigby, & Di Maio, 2011) have been recently developed and have proven promising. Also, ABM can create a platform for incorporating other methodologies such as game theory (Unsal & Taylor, 2010) and benefiting from them.

- Having a virtual laboratory of the system provides modelers with the ability to conduct experiments under various scenarios with little effort. Experimentation is the standard method of doing science particularly in management and social sciences where conducting experiments is impossible or undesirable (Gilbert, 2008). ABM as a scenario analysis tool provides owners and contractors with the ability to examine the possibilities as well as the probabilities of different conditions that could not be otherwise evaluated. With covering a range of possibilities and examining consistency of the results across a variety of scenarios ABM helps ensure obtaining robust conclusions.

- ABM can be used for performing ex-ante analysis of complex systems. Classical analysis tools such as statistical methods and game theoretic models have mostly failed addressing problems in which complexity and adaptation are core (Bankes, 2002).
- Complex systems generally represent important phenomenon called "emergence". In a complex system, agents' behaviors may be simple, but the aggregate patterns at the system level arisen out of their interactions can be complex and irreducible to the system's constituent parts. While this property is difficult to capture through mathematical and analytical approaches, ABM has shown great potential in dealing with such phenomenon (Bonabeau, 2002). Therefore, aggregate properties of a complex system are interpreted as emerging due to repeated interactions among agents rather than from the consistency requirements of rationality and equilibrium imposed by the modeler (Dosi & Orsenigo, 1994).

The construction bidding environment is a perfect example of an interactive, dynamic and complex system of heterogeneous and autonomous agents (contractors and owners). The complexity of this environment can be captured through a bottom-up modeling approach that focuses on the interactions among the agents. In the following section, the methodology for modeling and analyzing construction bidding environment will be introduced and discussed.

3.3. Methodology: A System-Of-Systems Approach

As explained in the previous chapter, the construction industry is a multi-level complex system where a collection of autonomous and heterogeneous agents, including but not limited to policy makers, public and private owners, developers, financiers, architects, designers, consultants, general contractors, subcontractors, and suppliers interact with each other at different levels. Construction bidding environment, where construction service suppliers meet the demanders, is a one of the major sub-systems of the construction industry system-of-systems.

This sub-system also can be viewed as a system-of-systems because the traits of the construction bidding environment match the generic, principal traits of a system-of-systems. These traits include managerial independency, operational independency, geographic distribution, heterogeneity, multilevel network structure, evolutionary behavior, and emergent behavior (Daniel DeLaurentis, 2005a; D. A. DeLaurentis, Crossley, & Mane, 2011). Following a system-of-systems analysis approach, as introduced by (Daniel DeLaurentis, 2005a), the proposed methodology used in this chapter for modeling construction markets consists of three phases: (1) definition, (2) abstraction, and (3) implementation.

3.3.1. Definition Phase

This phase mainly includes identification of the domain and context of the modeling. This phase is basically a mental mapping activity of construction bidding environment as a system-of-systems. In defining the model, we intend to employ and build upon the "proto-method" initiated and detailed by (Dan DeLaurentis & Callaway, 2004) including the lexicon and taxonomy proposed therein. Table 3.1 elaborates on the three levels of the construction bidding environment in four dimensions of resources, operation, policy, and economics known as ROPE (Dan DeLaurentis & Callaway, 2004). This representation of construction bidding environment is more limited and less comprehensive than the one representing the construction industry. The problem that the model is trying to address is specific to the interaction among contractors and owners in the bidding environment and during execution of projects. When applying a system-of-systems framework to the construction bidding environment, it is noteworthy to consider that construction project at the lowest level of the hierarchy is a temporary economic activity. Also, the collection of lower level entities (say construction projects at α level) and their connectivity determine the construct of an upper level network (a β-level network in this case). This is valid since construction firms are often called project-based organizations.

Table 3.1. The ROPE of the Construction Bidding Environment

Levels		Resources	Operation	Policy	Economics
α	**Project**	Money, material, manpower & machinery	Management of the project resources	All regulations and standards (safety, environmental, etc.) applied to the project	Economics of a project: accounting, cost management, budget control
β	**Organization**	collection of resources and assets for running the organization	Business / Project Portfolio Management	Policies relating to the organization (ex. tax exemptions, technical/ managerial eligibility & bonding capacity)	Owner: Project Evaluation, Delivery System Contractor: Bid/No Bid, Cost estimation, Pricing, Bidding Strategy
γ	**Market**	Multiple organizations working together based on contractual & non-contractual relationships	Competition/ Collaboration among organizations	Policies relating to the construction sector (incentives for reducing GHG emissions)	Economics of the sector

The developed model for construction bidding environment covers three levels of the construction industry: project, organization, and market. However, the major focus is on decisions and behaviors of agents at β-level and their interactions at γ-level. These levels were highlighted in Table 3.1. The impacts of project elements (such as cost) on agents at organization level are considered but analyzing interactions at project and organization levels (such as interaction between general contractors and subcontractors) is out of the scope of this model. The context of the modeling is to develop a bottom-up model of construction markets.

3.3.2. Abstraction Phase

The abstraction phase embraces the concept of object-oriented thinking, derived from the domain of computer programming. This phase facilitates transition from the definition phase to the implementation phase and subsequent validation and verification by encapsulating big-picture dynamics (Daniel DeLaurentis, 2005a). It includes identification of main classes of players, actions, and interrelationships within and across the levels of the model. There are basically two classes of players: owners (public and private) and contractors. It is assumed that contractors obtain their jobs from the demand available in the market by owners. According to (Rice & Heimbach, 2007), about 99% of the construction work by contractors is generated from owners in the industry. Table 3.2 explains the players' functions and goals in more details.

Table 3.2. Players of the model

Stakeholders		Descriptions	Goals
Owner	Public	having a pre-determined budget to initiate and manage new projects; being required to follow the governmental policies & regulations such as using low-bid system	meeting public needs; being within budget
	Private	making new investments depending on the market conditions; having flexibility to use other bidding systems	profit (long term/ short term); client's satisfactions
Contractor		selling services to owners; managing resources	profit; market share; job continuity; etc.

Each single player of any class has its own goals, priorities, decision rules, learning capabilities, and other attributes. According to (Russell & Norvig, 1995) agents can be grouped into five classes based on their degree of perceived intelligence and capability:

1. simple reflex agents,
2. model-based reflex agents,
3. goal-based agents,
4. utility-based agents, and
5. learning agents.

Depending on the purpose and level of details needed for an experiment, an agent contractor can be designed and placed in one of these five classes.

Because the focus of this study is on contractors' interaction with each other and the market, an abstraction of a contractor in the bidding environment is presented in Figure 1. It is worth noting that the agent–environment boundary represents the limit of the agent's absolute control, not of its knowledge. An agent contractor makes decisions based on the short-term and long-term goals as well as beliefs, knowledge and information obtained from the market and opponents. After implementing the decisions, the agent observes the outcomes, updates the information and refines knowledge and beliefs for further decisions to be made. Under certain conditions, beliefs, knowledge and information can change a contractor's goals. For example, expecting a decline in construction demand may convince a contractor to change its objective from pure profit maximization to a combination of profit maximization and work continuity.

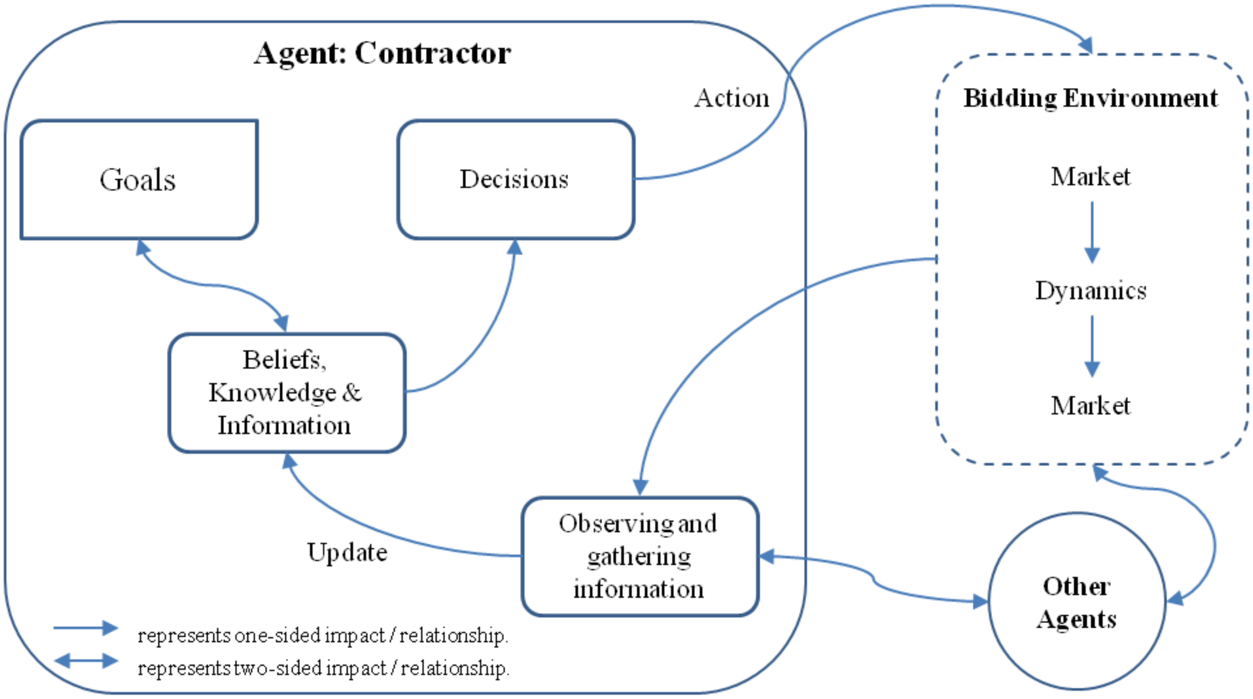


Figure 3.1. An abstraction of a contractor in the bidding environment

3.3.3. Implementation phase

AnyLogic 6.7.0 (XJTechnologies, 2011), a Java based ABM platform, is used to implement the conceptual model introduced in the previous phases and create a computational laboratory. Following the abstraction phase, the classes of agents in the model include owner and contractor, each of which is simulated in the model as an active object. The model also includes another active object class called project which has its own Statechart and Methods but has no decision making and learning ability, making it a passive agent, or a pseudo-agent. Object oriented programming enables us to have whatever number of active objects we need by defining them as replicated objects. Therefore, a desired experiment can be run and repeated with different number of owners, contractors, and projects. In the following subsections, the components of the model are explained in further detail.

3.3.3.1. The Big Picture of the Simulation

The simulation model aims to reproduce the bidding environment with more focus on main decision points of contractors at organization level. Figure 2 shows a schematic representation of the simulation model. The mechanism of the simulation is that a set of heterogeneous contractors bid on a series of projects of different types and sizes randomly generated by various owners. Similar to a deductive approach, a set of axioms are assumed to build the model. However, these assumptions are more general and more flexible than strong assumptions used in the literature. For example, in contrast to the deductive category of the literature, in this model a variety of goals and behaviors can be defined for contractors. Finally, data from the simulation is gathered and can be analyzed using an inductive approach.

This section is aimed to explain the details of the virtual laboratory to the degree that is necessary for understanding the big picture of the simulation. Indeed, further parameters, variables, methods, and other components can be added to the model in order to run a specific experiment.

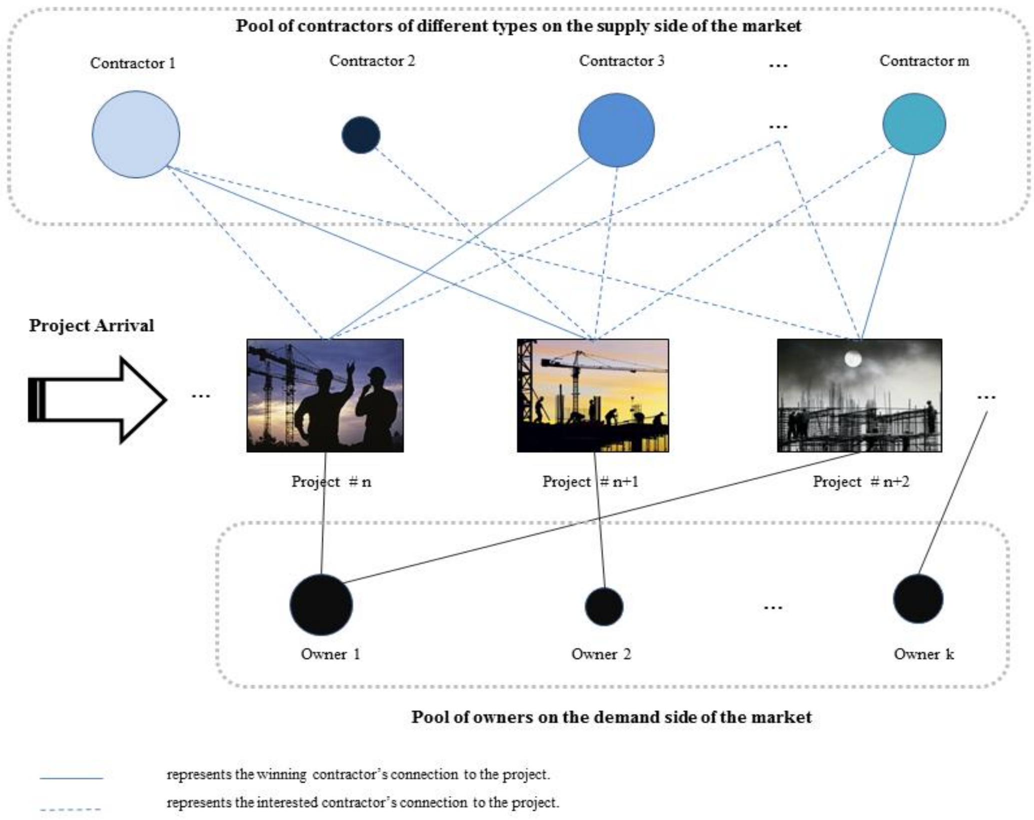


Figure 3.2. Network structure of the construction bidding environment

3.3.3.2. Active object: Owner

The main actions of an owner are to generate projects and choose their associated bidding systems. The experiment to be conducted in this study only considers owners who use a low bid system and lump-sum contracting method for delivering their projects. The number of projects generated by an owner in a time interval can take any distribution (e.g. Poisson Process). The rate of project generation can represent the current condition of construction demands; the higher the rate the more potential contracts.

3.3.3.3. Active object: Contractor

Figure 3.3 presents agent contractor as an active object in AnyLogic platform. Each contractor has a number of attributes and parameters including initial bonding capacity, net worth, specialty, risk aversion coefficient, current work volume and the maximum number of projects a contractor can work on at one point in time, indicated as work in progress limit, general & administrative costs, etc. A contractor also has its own functions when it comes to decision or action points. Shall bid decision and markup decision are among the most vital decisions that a contractor has to make. Generally, a contractor decides whether to bid or not for a specific project depending on various internal and external factors. In this study, a function called “shallBid” was developed to simulate the decision to bid on a certain project by a contractor and which takes into account level of the project complexity, required specialization for the project, its current work volume, and its available bonding capacity. Since the project contracting method is lump-sum, the interested contractor uses a function for determining the estimated cost of the project. This function is called “costEstimation” and samples the cost estimate of a contractor from a distribution.

One of the most important questions in construction bidding environment is how contractors choose their markup. As discussed in the background section, several markup decision models exist in the literature. The applied markup decision models in each simulation experiment will be explained in the related chapter. In general, the contractor’s “markup” function serves to find the markup that optimizes the contractor’s goal at that moment of the simulation. It can be either maximizing the expected utility of profit from a certain project or fulfilling some certain sub-goals such as need for work.

There are other decisions that an agent contractor can make during the simulation including decisions for: 1) expanding the business which results in more resources for securing new projects and higher indirect cost for the firm; 2) contracting which limits capability to have more projects at a time; 3) entering a new market; 4) quitting a market; 5) acquiring a new technology or specialty; and 6) changing risk attitude and organizational culture.

Using “Collections” in AnyLogic, agent contractors can gather, update, and store data and feedbacks from the environment. These collections are referred in functions and Statecharts so that a contractor can use the latest information about other contractors and the environment.

Different Statecharts can be defined and used for an agent contractor. With respect to the financial state, a contractor can be in one of the four Statecharts at any time during the simulation: 1) Normal State; 2) Panic State; 3) Desperate State; and 4) Bankrupt State. If a modeler finds it necessary, the markup function or other decision functions of contractors can be linked to their financial state (Mahdavi & Hastak, 2014).

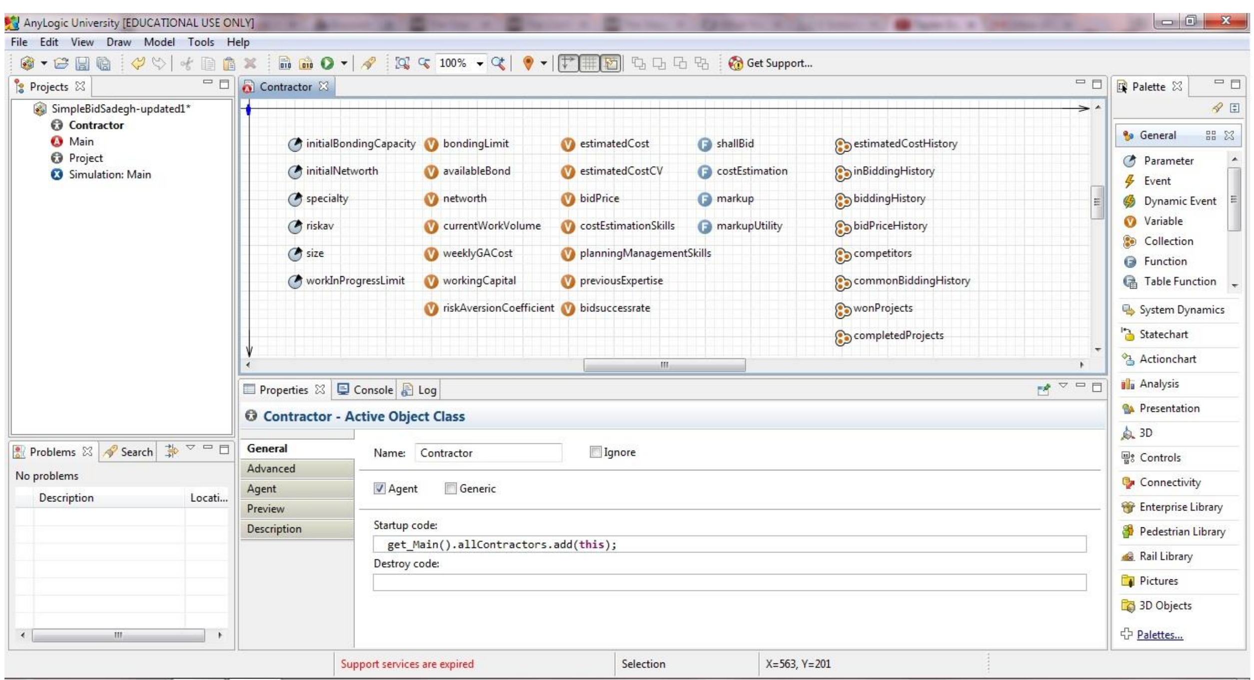


Figure 3.3. Contractor defined as an active object in AnyLogic

3.3.3.4. Active object: project

Each project has a number of attributes including project type, estimated budget, estimated duration, and complexity level that are set once a project is generated (Figure 3.4).

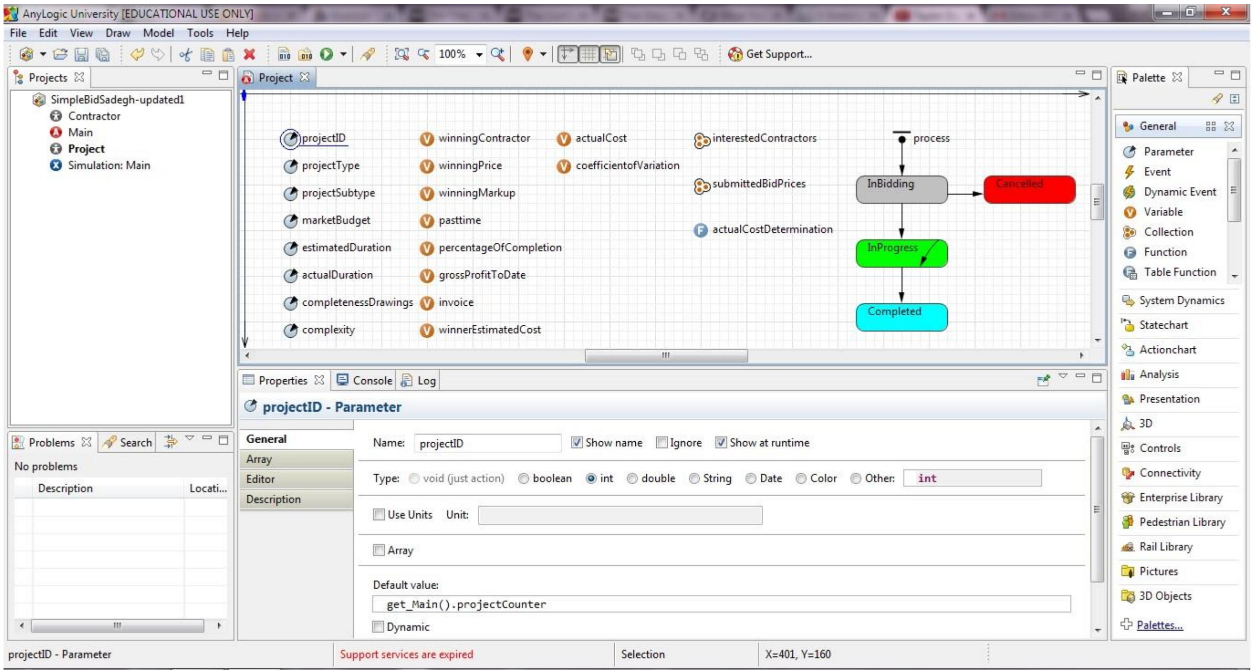


Figure 3.4. Project defined as an active object in AnyLogic

Moreover, a project has a Statechart that simulates the major stages of its lifecycle. As shown in Figure 3.5, it consists of four states: InBidding, InProgress, Completed, and Canceled. A project is in the state “InBidding” once it is generated by its owner. Contractors observe the project and decide to bid or not based on their function “shallBid”. Then, interested contractors determine their bids based on their functions “costEstimation” and “markup”. If certain criteria such as minimum interested contractors are met, the winner is determined and the project gets started by going to the state “InProgress”. Otherwise, the project is canceled by the owner and goes to the state “Canceled”. In order to track and update the financial status of a contractor throughout the simulation, we need to assign an actual cost value to any project he wins. Hence, a function was created under the project class, “actualCostDetermination”, which determines the actual cost of a project based on the project complexity and the winning contractor’s planning and managerial capabilities. The difference between the winning bid price and the actual project cost in addition to the general and administrative expenses, which is the profit/loss of the winning contractor in this project, gradually adds to the net worth of the contractor according to the project’s percentage of completion. The percent completion is determined following a rule of thumb S-curve that links cost expenditure with project timeline assuming one quarter of the cost spent at one third of the project time and three quarters of the cost incurred at two thirds of the time (Miller, 1962). Finally, the project goes to the state “Completed” when it is finished.

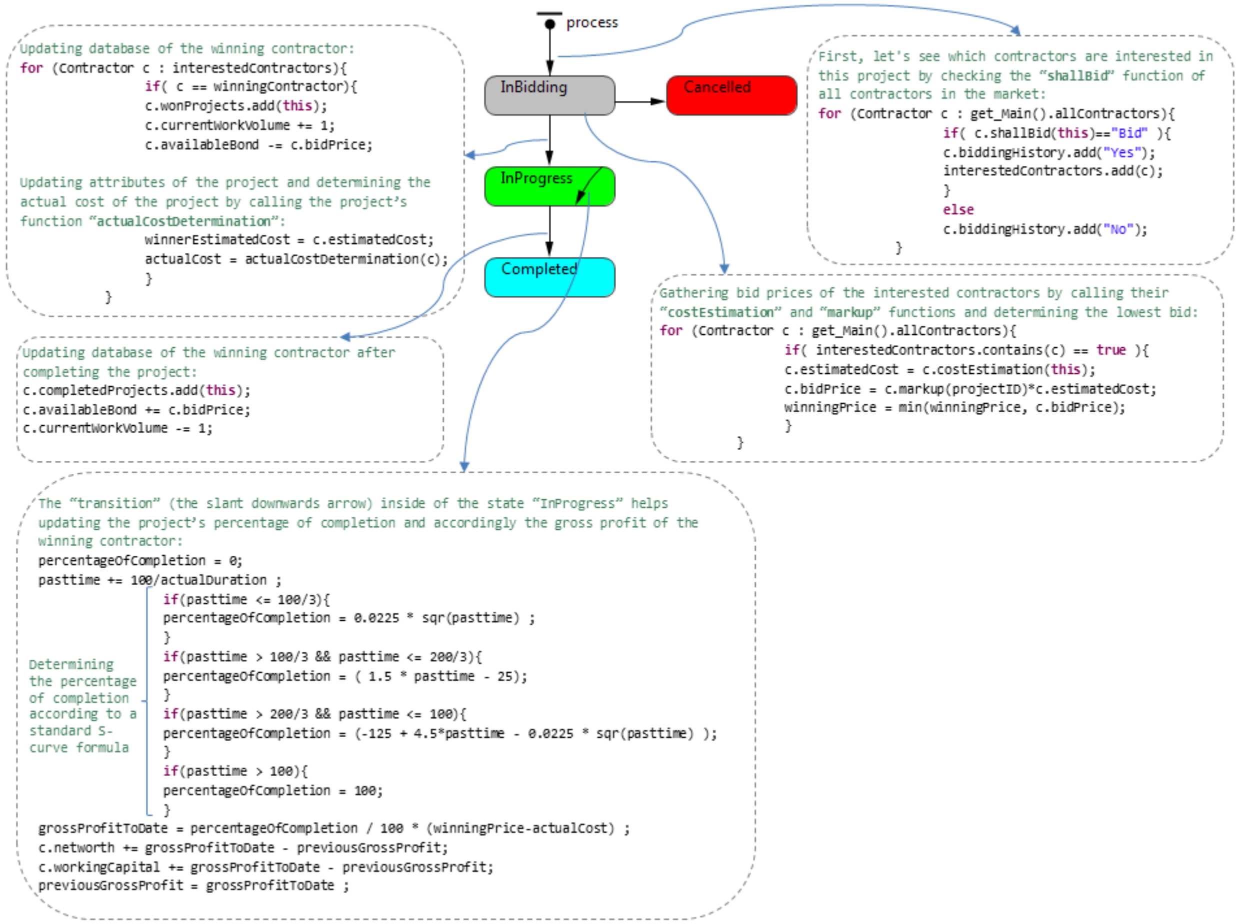


Figure 3.5. Statechart used to define different stages of a project

3.4. Assumptions and Boundaries of the Model

This section presents all assumptions and boundaries of the model that are applied to all experiments in Chapter 4, 5, and 6 as it follows:

- The agent-base model is specifically developed to simulate the low-bid lump-sum bidding process although it can be used for other types of bidding (such as A+B bidding method) with little modifications.
- The model does not take into account behavior of the owner. It only assumes that owners use the low-bid lump-sum bidding method to allocate their projects.

- Projects are generated one at a time for 520 time units which is equal to 10 years (520 weeks).
- In this study, risk is defined as the possibility that the actual cost of a project will be higher than the estimated cost due to internal or external factors.
- A more risk averse contractor means a contractor that considers and adds a higher allowance to the markup to cover the possible loss.
- Contractors in the market will remain the same throughout the simulation in the experiments conducted in Chapter 4, 5, and 6.
- The "costEstimation" function determines the estimated cost of a project for a contractor given the estimating accuracy of the contractor. This study assumes the estimated cost is triangularly distributed around the project budget and there are two levels of estimating accuracy: Normal and Improved. If the estimating accuracy is normal (or improved), the variation of estimated cost can be up to 10% (or 5%) of the project budget.

```
if (estimatingAccuracy == "Normal")
       {estimatedCost = pert(0.90, 1.10, 1.00)*p.marketBudget;
       }
else if (estimatingAccuracy == "Improved")
       {estimatedCost = pert(0.95, 1.05, 1.00)*p.marketBudget;
       }
return estimatedCost * (1+GAPercentage);
```

- The "actualCostDetermination" function determines the actual cost of a project for a contractor based on the project execution skills of the contractor and level of the project complexity.

```
if (complexity == 3)
{ if (c.projectExecution == "Normal")
       {actualCost = triangular(1.05,1.15,1.1)*c.estimatedCost*(1-c.GAPercentage);
       }
  else if (c.projectExecution == "Improved")
     {actualCost = triangular(1.025,1.125,1.075)*c.estimatedCost*(1-c.GAPercentage);
     }
 }
```

```
else if (complexity == 2)
{ if (c.projectExecution == "Normal")
       {actualCost = triangular(1.0,1.1,1.05)*c.estimatedCost*(1-c.GAPercentage);
       }
  else if (c.projectExecution == "Improved")
     {actualCost = triangular(0.975,1.075,1.025)*c.estimatedCost*(1-c.GAPercentage);
     }
 }

else if (complexity == 1)
{ if (c.projectExecution == "Normal")
       {actualCost = triangular(0.95,1.05,1.0)*c.estimatedCost*(1-c.GAPercentage);
       }
  else if (c.projectExecution == "Improved")
     {actualCost = triangular(0.925,1.025,0.975)*c.estimatedCost*(1-c.GAPercentage);
     }
 }

return actualCost;
```

- The progress of a project follows a S-curve formulated by (Miller, 1962).

3.5. Chapter Summary

This chapter presented a comprehensive literature review of major scientific studies in the field of competitive construction bidding and categorized them into three main classes of induction, deduction, and simulation according to their methodological approach. After identifying the gap in the literature, using a System-of-Systems approach this chapter explained development of an agent-based model of the construction competitive bidding process where contractors with different characteristics and attitudes compete against each other over projects with different attributes, learn about each other, and make bidding decisions accordingly. This model has several advantages over the previous analytical and empirical models including the capability of observing the bidding process dynamics, the interaction between the heterogeneous and learning agents, and the emergent bidding patterns arising from multiple scenarios of market conditions and contractors' attributes. This model can serve as an experimental laboratory that can be used by any potential user (owner or contractor) to evaluate and compare different bidding strategies and project tendering approaches. The model capability to replicate the construction market can be enhanced further through adding necessary components. The developed laboratory can also serve as an educational tool in academic forums and classes to teach construction management students about the bidding process and all its complexities and to allow them to observe interesting dynamics and interactions between the different market constituents from an outsider's perspective.

CHAPTER 4. ANALYSIS OF QUANTITATIVE BIDDING METHODS: TOWARDS HETEROGENEITY IN LEARNING AND UNCERTAINTY

"Information is a source of learning. But unless it is organized, processed, and available to the right people in a format for decision making, it is a burden, not a benefit." ~ William Pollard

4.1. Introduction

As explained in chapter 3 (development of the virtual laboratory), one of the major components of the developed virtual laboratory is the markup decision function. Among all, competition has been identified as one of the main decision criteria for construction contractors when bidding for a project (Hegazy & Moselhi, 1995). Real world contractors try to learn about their competitors' bidding strategy so do the simulated contractors in the virtual laboratory. In the real world bidding environment, learning mechanisms vary from one construction contractor to another. Some are more inclined to use quantitative approaches while others rely on more rule-based or judgment-based decision making tools.

Regardless of the type of the learning mechanism and bidding decision making tool, the underlying assumption in all bidding calculation is that there exists a relationship between the bid sum and the probability of winning the project. The bid sum is the product of the estimated costs and the markup percentage. Therefore, there are two extreme points when determining the markup. The lower the markup, the higher chance of winning (or the lower profit) is. Conversely, the higher the markup, the lower chance of winning (or the higher profit) is.

There are several quantitative methods in the literature and the next section will present a review of the major studies in this area. Although quantitative methods have received a lot of attention in the literature, the debate over their validity and effectiveness, in particular Friedman and Gates models, have not reach a solid conclusion. This chapter will take a new approach to compare these methods. First, these methods are coded in the model as the markup decision function for agent contractors. In other words, they are the learning mechanisms of agents in an interactive environment. Then, using the developed virtual laboratory, these methods can be put in a competition against each other. The objective of this chapter is to compare the effectiveness of major quantitative methods in the bidding environment under a variety of scenarios including low to high level of uncertainty in the estimated cost and different types of market limitations. Previous studies in the literature that analyzed and compared these methods mostly take a retrospective approach. In other words, they compare these methods one by one in a vacuum using past bid data. However, thanks to the virtual laboratory, the possibility of comparing these methods actively and in a prospective manner exists. This study tries to address the lack of practical testing due to unwillingness of contractors to reveal their real bid information and costs.

This chapter is organized as follows: the “Literature on Quantitative Bidding Methods” section reviews the major contributions in the area of quantitative bidding models. The “Methodology & Description of Experiments” explains the experiments that will be conducted in this chapter. The “Results” section will present the main observations on the experiments and discuss their root-causes. Finally, the “Chapter Summary” section summarizes key findings of the study.

4.2. Literature on Quantitative Bidding Methods

A quantitative method tries to use competitors’ past bids to determine the optimal markup. The optimal markup is usually defined as the one that maximizes the expected profit of a contractor from a given project. In other words, a contractor is facing the following optimization problem where he is trying to balance a great profit and a high probability of winning:

$$max\, E[Profit(x)|\, x, n] = max\, Probability(Winning|\, x, n)\ \times Profit(x) \qquad (4.1)$$

Where x: $markup$ % is the decision variable of the problem and the expected profit, is the product of the probability of winning and the profit given a chosen markup. It is worth noting that the bid (B), estimated cost (ES), markup (x), and profit have the following relationships for a given project k:

$$B_k = ES_k(1 + x_k) \qquad (4.2)$$

$$Profit_k = ES_k . x_k \qquad (4.3)$$

Several quantitative methods exist in the literature. For any quantitative method there are at least three basic uncertain variables (estimated cost, actual cost, and the lowest competing bid) that need to be considered (Fuerst 1977). One of the first two (either variables estimated cost or actual cost) has to be fixed and selected as the reference point of modeling (Yuan 2011). The selected models in this chapter (Friedman, Gates and Fine) consider the estimated cost as the reference point and then the uncertainty of a competitor's bidding behavior is characterized by the bid ratio. It is worth mentioning that transparency of the market transactions, knowing who the interested contractors in the bid shortlist are, level of access to the previous biddings information, and contractors' willingness to collect and use the information are amongst underlying assumptions of all the three models. It is assumed that each interested contractor knows the other interested contractors in the bidding shortlist and knows their bids for those projects that both the opponent and the contractor previously participated in.

4.2.1. Friedman model

In his seminal paper entitled "A competitive-bidding strategy", (Friedman, 1956) proposed to use historical bid data and characterize a competitor's bidding behavior with a probability distribution function of the bid ratio. The bid ratio ($BC_{k,i}$) for a given project (k) is simply the ratio of the competitor i's bid ($B_{k,i}$) to the contractor's own estimated cost (ES_k):

$$BC_{k,i} = \frac{B_{k,i}}{ES_k} \qquad (4.4)$$

If competitor *i* and the contractor have enough bids where they both participated and the bid information is available, a stable distribution function ($F_X(x)$) of the bid ratio can be constructed. By calculating the mean and variance of the distribution, the probability of beating competitor *i* (P_i) with a given markup (*x*) can be simply calculated using the following equation:

$$P_i(x) = \Pr(X > x) = 1 - F_X(x) \qquad (4.5)$$

Friedman then assumed the bid ratios of competitors are independent of each other. Therefore, the probability of winning the contract, which means beating all competitors, can be determined using the following equation:

$$P_w(x) = \prod_{i \in Competitors} P_i(x) \qquad (4.6)$$

4.2.2. Gates model

This model calculates the probability of beating a competitor exactly in the same way Friedman does. However, based on his experience as a principal estimator, (Gates, 1967) developed the following equation for determining the probability of winning the contract.

$$P_w(x) = \frac{1}{1 + \sum_{i \in Competitors} \left(\frac{1 - P_i(x)}{P_i(x)} \right)} \qquad (4.7)$$

Where P_i is the probability of beating competitor i.

4.2.3. Fine model

The main assumption of this model (also known as the low-competitor model) suggested by (Fine) in a series of unpublished works is that the only competitor the contractor is interested in beating is the lowest competitor (in other words, the winner). Therefore, this model is based on collecting the historical data of the lowest bid, the winner, in each competition participated.

4.3. Methodology & Description of Experiments

Agent-based modeling is a great tool for conducting experiments and analyzing research questions under a variety of scenarios. By applying the quantitative bidding methods in a series of consecutive bids, agent contractors in the virtual laboratory are taking a computational approach to learning from their interactions with others. Agent contractors are not instructed to choose a specific markup. Instead, they are using different learning mechanisms (here, the quantitative bidding methods) to choose the optimal markup. Each learning mechanism represents some specific learning characteristics. Comparing the performance of users of these mechanism helps understand their applicability and effectiveness in various situations. The virtual laboratory developed in the Chapter 3 is used in this chapter for investigating the following research questions:

1- What is the impact of the choice of learning mechanisms on contractors' financial performance, success rate, and market share under a variety of market scenarios?

2- How do these learning mechanisms perform in markets with irrational, random, and unpredictable players?

3- How do these learning mechanisms perform in competition against each other and irrational players?

The six sets of experiments to be conducted in this chapter together address the above questions. Each experiment set contains several market scenarios.

Two main classes of objects in the simulation model are Projects and Contractors. Projects are passive agents and Contractors are active agents due to their ability to learn and make decisions. Projects are generated consecutively over a simulation period of ten years (520 simulated time units) and are assigned a set of characteristics such as the project budget chosen uniformly over the range [80, 120] M$ and the project duration also selected uniformly between 20 and 30 weeks. On the other hand, a set of contractors is produced in the market along with their learning mechanisms. Agent contractors are homogenous in all attributes except in their learning mechanisms. To ensure the consistency and reliability of the results each experiment has been run for 100 times.

4.3.1. Experiment Set A

The purpose of the first set of experiments is to find the impact of different learning mechanisms on the contractors' performance under a variety of cost estimation and contingencies scenarios. There are nine contractors competing with each other in the market including three contractors using Friedman model, three contractor using Gates model, and three contractors using Fine model. Table 4.1 shows the learning mechanism assigned for each of the nine contractors. In the first set of experiments, projects are generated in the market one at a time unit under different scenarios.

Table 4.1. Contractors' characteristics in experiment set A

Contractor	Learning Mechanism
1, 2, and 3	Friedman
4, 5, and 6	Gates
7, 8, and 9	Fine (the low-competitor)

Scenario A1 is a pure, non-limited competition among contractors. There is not a limitation on bonding; therefore, contractors can win and have as many as projects at a time they want. There are also no G&A costs as well as a low level of uncertainty on the estimated cost of projects (2.5%

inaccuracy). Contractors do not consider any contingencies in their estimated costs. Although the market conditions and settings seem unrealistic in this scenario, the result will be insightful and interesting to know.

Everything under scenario A2 is similar to the scenario A1 except the fact that level of uncertainty on the estimated cost of projects will be high (5% inaccuracy).

Scenario A3 takes the simulation one more step closer to the reality by adding contingencies to the process of cost estimation. It is assumed that contractors add enough contingencies for dealing with uncertainty in the estimated cost. Everything under this scenario is similar to the scenario A1 except the fact that contractors consider contingencies when estimating their costs.

Everything under scenario A4 is similar to scenario A2 except the fact that contractors consider contingencies when estimating their costs.

4.3.2. Experiment Set B

The purpose of the second set of experiments is to investigate the impact of different levels of bonding capacity on performance of contractors with different learning mechanisms. Setting of experiment set B is the same as experiment set A. In experiment set B, scenarios B1 to B7 will cover a range of limitations on the number of ongoing projects contractors are allowed to have at any time during the simulation. This limitation simulates the bonding capacity of contractors in the real world bidding environment. To maintain market competition, it is assumed that having a minimum number of two participants is required for a bid to be valid. Otherwise, it will be cancelled. Table 4.2 presents the number of ongoing projects allowed for contractors under scenarios B1 to B7.

Table 4.2. Number of ongoing projects allowed for contractors under scenarios B1 to B7

Scenario	B1	B2	B3	B4	B5	B6	B7
Number of ongoing projects allowed	8	7	6	5	4	3	2

4.3.3. Experiment Set C

The purpose of the third set of experiments is to examine capability of different learning mechanisms dealing with unpredictable competitors. In the experiment set C, a learning mechanism is used by only one contractor competing with 8 other contractors that are choosing their markup randomly from uniform distribution of [0% - 10%]. These contractors are called “Random Contractors” hereafter. In order to be able to compare performance of different learning mechanisms, project budget is set to be M$100. Level of uncertainty on the estimated cost of projects is low (Scenario C1) and high (Scenario C2) and all contractors consider contingencies in their submitted price. There is no limitation on number of ongoing projects that a contractor can have.

4.3.4. Experiment Set D

The purpose of the fourth set of experiments is to examine capability of different learning mechanisms competing in a mixed market comprising of both learning contractors and random contractors for securing project with two levels of cost estimation uncertainty. In experiment set D, the market includes a mix of contractors using three main learning mechanisms and random markup. Table 4.3 presents markup function of each contractor. Similar to the experiment set C, level of uncertainty on the estimated cost of projects is low (Scenario D1) and high (Scenario D2).

Table 4.3. Contractors' characteristics in experiment set D

Contractor	Learning Mechanism
1 and 2	Friedman
3 and 4	Gates
5 and 6	Fine (the low-competitor)
7 and 8	Nothing (Random Markup)

4.3.5. Experiment Set E

The purpose of the fifth set of experiments is to investigate the impact of different levels of bonding capacity on performance of both learning contractors and random contractors. Table 4.4 presents the number of ongoing projects allowed for contractors under scenarios E1 to E9. Market consists of heterogeneous contractors as Table 4.3 and the uncertainty in cost estimation is high.

Table 4.4. Number of ongoing projects allowed for contractors under scenarios B1 to B7

Scenario	E1	E2	E3	E4	E5	E6	E7	E8	E9
Number of ongoing projects allowed	10	9	8	7	6	5	4	3	2

4.3.6. Experiment Set F

The purpose of the sixth set of experiments is to investigate the impact of requiring minimum number of contractors participated in bidding on performance of contractors and the market. Imposing minimum number of contractors required in a bid is a strategy for clients to maintain a desirable level of competition. However, the impact of this requirement is not explored well.

In this experiment set, it is assumed that contractors are allowed to have only five projects in progress at a time. As Table 4.5 presents, different values are assigned to the minimum number of bid participants required by the clients. Market settings and contractors characteristics are similar to experiment set E.

Table 4.5. Minimum number of bid participants required in scenarios F1 to F5

Scenario	F1	F2	F3	F4	F5
Minimum number of bid participants required	4	5	6	7	8

4.4. Results

4.4.1. Results of Experiment Set A

The results of scenario A1 are presented in Table 4.6. A significant separation is observed in the performance of the three groups of contractors (users of Friedman, Gates, and Fine models). One interesting observation is that the average of markup determined by contractors is very low (0.47%, 0.86%, and 1.44% for Friedman users, Fine users, and Gates users respectively). This is mainly because of relatively high number of sophisticated, rational competitors in the market. Once a contractor brings down its price to win the next contract, its competitors observe this action and will reciprocate it with lowering their price. This tug of war will continue until the market reaches equilibrium. Markups of the contractors stayed almost constant after the first year of the simulated time (52 time units).

Freidman users have shown higher bid success rates comparing to others, resulted in higher market shares. The order of contractors in terms of market share is: Friedman users > Fine users > Gates users. However, having a higher bid success rate did not result in a better financial performance.

Under this scenario, all contractors have faced financial loss because of mainly two reasons: 1- none of the contractors had considered contingencies in their cost estimation. 2- the winner of a bid may not be just the most competitive one in terms of markup but also most probably the contractor with a very low estimated cost (in other words, the one who made the biggest mistake). The order of contractors in terms of working capital is: Gates users > Fine users > Friedman users. It is worth noting that in this scenario, the success rate was equal to the market share since all contractors were participated in all bids.

Table 4.6. Contractors' performance in scenario A1

Contractor	Working Capital (M$)	Profit per Project (M$)	Market Share
1	(117)	(1.33)	17%
2	(152)	(1.43)	20%
3	(141)	(1.34)	20%
4	(14)	(0.58)	5%
5	(12)	(0.71)	3%
6	(10)	(0.68)	3%
7	(55)	(1.03)	10%
8	(62)	(1.08)	11%
9	(62)	(1.11)	11%

The results of scenario A2 are presented in Table 4.7. Orders and trends in the results of scenario #2 are similar to ones in scenario A1. However, the average markup determined by contractors in this scenario (0.85%, 1.51%, and 2.81% for users of Friedman, Fine, and Gates respectively) is higher than the ones in scenario A1. This can be because of higher uncertainty in the estimated costs that results in higher variance in the bid to cost ratio. Also, comparing working capital and profit per project in Table 4.6 and Table 4.7, one minor difference between the scenarios A1 and A2 is that the size of loss for all contractors is larger under scenario A2 because of the higher uncertainty in cost estimation.

Table 4.7. Contractors' performance in scenario A2

Contractor	Working Capital (M$)	Profit per Project (M$)	Market Share
#1	(264)	(2.87)	18%
#2	(322)	(3.06)	20%
#3	(293)	(2.81)	20%
#4	(31)	(1.49)	4%
#5	(23)	(1.43)	3%
#6	(28)	(1.39)	4%
#7	(136)	(2.44)	11%
#8	(150)	(2.50)	12%
#9	(101)	(2.16)	9%

The historical volatilities of the market markup for all 10 years of the simulation under both scenarios (A1 and A2) were calculated and provided in Table 4.8. The historical volatility (HV) of a time series can be calculated by determining the average deviation from the average value of the variable in the given time period. HV is provided in two scales: one-week HV because the time unit in the simulation is one week and annualized HV because the performance of most firms are being evaluated on the basis of a year in the real world. One-week HV is in fact the standard deviation of the changes in the market markup ($y_i, i \in \{1, \dots, 52\}$). The change in market markup (*y*) can be calculated in the both following ways:

$$y_i = \ln\left(\frac{MM_i}{MM_{i-1}}\right) \qquad (4.8)$$

Or

$$y_i = \left(\frac{MM_i}{MM_{i-1}}\right) - 1 \qquad (4.9)$$

Where MM_i is the market markup in day *i*. The equations for calculating the annualized HV is simply:

$$\text{Annualized HV} = (\text{One} - \text{week HV}) \times \sqrt{52} \qquad (4.10)$$

As it can be easily seen in Table 4.8, one major difference between the scenarios #1 and #2 is the larger volatility of market markup under scenario #2 due to the higher uncertainty and inaccuracy in the estimated costs.

Table 4.9 presents the results of the experiment set A3. As expected, the average markup determined by contractors in this scenario (0.85%, 1.51%, and 2.81% for users of Friedman, Fine, and Gates respectively) is very low (similar to scenario A1). Considering contingencies helps all contractors make profits from their won projects. Therefore, a higher bidding success rate and consequently market share can increase the working capital. However, Profit per project in this scenario has still the same order as it does in scenario A1. Gates users do not win as often as Friedman users and Fine users but when they win, they earn a larger profit.

Table 4.8. The historical volatilities of the market markup

	Scenario A1		Scenario A2	
Year	One-week HV	Annualized HV	One-week HV	Annualized HV
1	0.49%	3.52%	0.89%	6.41%
2	0.54%	3.90%	0.99%	7.14%
3	0.51%	3.66%	0.70%	5.03%
4	0.31%	2.23%	0.60%	4.33%
5	0.32%	2.30%	0.75%	5.38%
6	0.52%	3.75%	0.91%	6.55%
7	0.44%	3.14%	1.02%	7.37%
8	0.47%	3.41%	0.96%	6.91%
9	0.49%	3.55%	0.86%	6.21%
10	0.48%	3.48%	0.97%	7.00%

Table 4.9. Contractors' performance in scenario A3

Contractor	Working Capital (M$)	Profit per Project (M$)	Market Share
1	103	1.02	19%
2	119	1.21	19%
3	124	1.16	21%
4	30	2.02	3%
5	45	1.89	5%
6	33	1.86	4%
7	70	1.49	9%
8	86	1.51	11%
9	70	1.30	10%

Table 4.10 presents the results of scenario A4. Similarities and differences between this scenario and scenario A3 are consistent with the ones between scenarios A1 and A2. For example, the working capital and profit per project have increased for all contractors due to the higher uncertainty in cost estimating. Also, volatility of market markup is higher under scenario A4.

Table 4.10. Contractors' performance in scenarios A4

Contractor	Working Capital (M$)	Profit per Project (M$)	Market Share
1	184	1.95	18%
2	223	2.10	20%
3	225	2.28	19%
4	68	3.58	4%
5	70	3.67	4%
6	53	3.53	3%
7	121	2.16	11%
8	146	2.70	10%
9	159	2.70	11%

4.4.2. Results of Experiment Set B

Tables and figures in this section present different information and performance indicators of contractors and the market. Number of contractors participating in biddings is one of the main factors influencing the level of competition in construction biddings. The higher the number of participants the more fierce the competition will be. As Table 4.11 shows the average and minimum number of contractors in biddings has decreased from scenario B1 to scenario B7 due to imposing limitation of bonding capacity. This limitation has also caused cancelation of 42 and 182 projects under scenarios B6 and B7 (respectively) where contractors have reached their quota and were not able to participate in some of the biddings, resulted in the cancelation.

Table 4.11. Market information of scenarios B1 to B7

Scenario	B1	B2	B3	B4	B5	B6	B7
Maximum number of ongoing projects allowed	8	7	6	5	4	3	2
Average number of contractors participating in biddings	8.9	8.7	8.2	7.6	6.1	3.4	2.1
Minimum number of contractors participating in biddings	7	7	6	5	3	1	1
Number of cancelled projects	0	0	0	0	0	42	182

One interesting observation presented in Table 4.12 is that the average markup of all contractors and volatility of the markup market have increased from scenario B1 to scenario B7. The variance in the market markup basically resulted from the micro behavior of Friedman and Gates users. Submitted markup of Friedman and Gates users have increased partly due to the decrease in number of competitors in bids. However, submitted markup of Fine users is getting almost constant after several bids and has shown much less increase compared to the ones of Friedman and Gates. This is mainly due to the fact that Fine model is non-sensitive to any specific contractor's behavior and number of contractors participating in the bid.

Table 4.12. Average markup of contractors and volatility of the market in scenarios B1 to B7

Scenario	B1	B2	B3	B4	B5	B6	B7
Average Markup of Friedman Users	0.81%	0.83%	0.90%	0.96%	1.26%	2.59%	4.43%
Average Markup of Gates Users	2.56%	2.74%	2.71%	2.77%	2.80%	4.07%	5.76%
Average Markup of Fine Users	1.50%	1.43%	1.63%	1.55%	1.53%	1.80%	1.91%
Average Markup of the Market	1.62%	1.66%	1.75%	1.76%	1.86%	2.82%	4.03%
One-Week Historical Volatility of Market Markup	0.82%	0.85%	0.85%	0.88%	0.90%	1.06%	1.18%
Annualized Historical Volatility of Market Markup	5.91%	6.15%	6.13%	6.35%	6.45%	7.63%	8.48%

Observing Figure 4.1, the increasing trend of profit per project for all contractors in the market under scenarios B1 to B7 suggests that abundance of projects caused inflation in contractors' submitted markup and consequently their bids. While the usual order of contractors in terms of profit per project is Gates users > Fine users > Friedman users, this order is changed in case of scenario B6 and B7. One explanation for Friedman users outperforming Fine users on this indicator under scenario B6 and B7 is that Friedman model is influenced by number of contractors and the bid history of each competitor whereas Fine model only take the market markup into consideration and ignores bid history of competitors. This consideration has made Friedman users more effective compared to Fine users, resulting in higher profit per project. For the same reason, it can be argued that the gap between average profit per projects of Gates users and Fine users has increased from scenario B1 to B7.

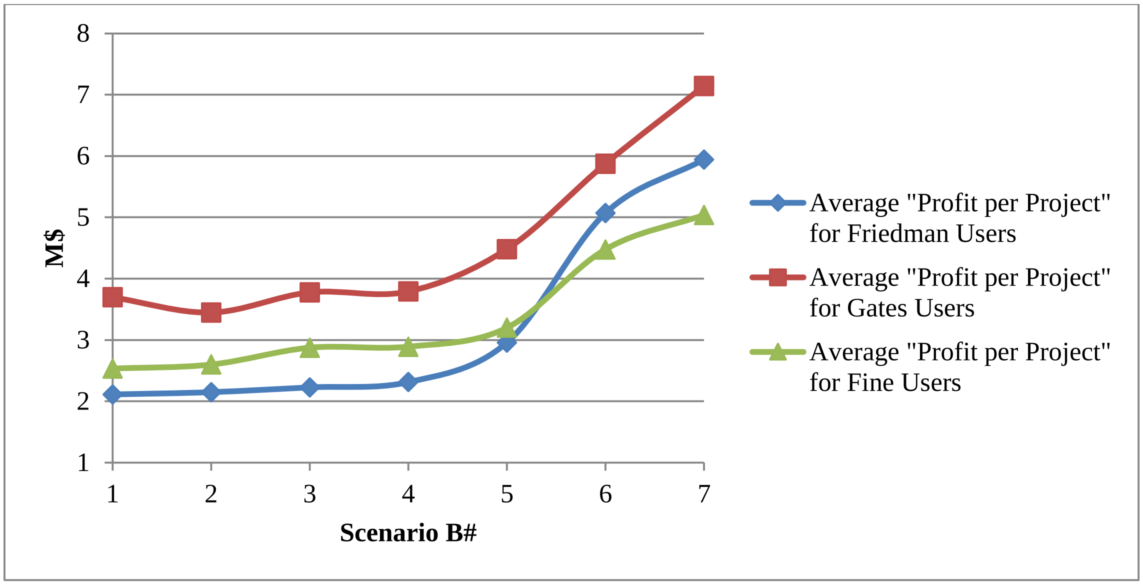


Figure 4.1. Project per profit of contractors in scenarios B1 to B7

As shown in Figure 4.2, imposing the limitation of bonding capacity has decreased market share of Friedman users and ended their dominance to the extent that the market is divided almost equally among all contractors in scenario B7. The main reason for the increase in bid success rate and market share of Gates users is the fact that Friedman and Fine users are winning more projects in the beginning and once some of them reached their quota Gate users have higher chance to secure more projects.

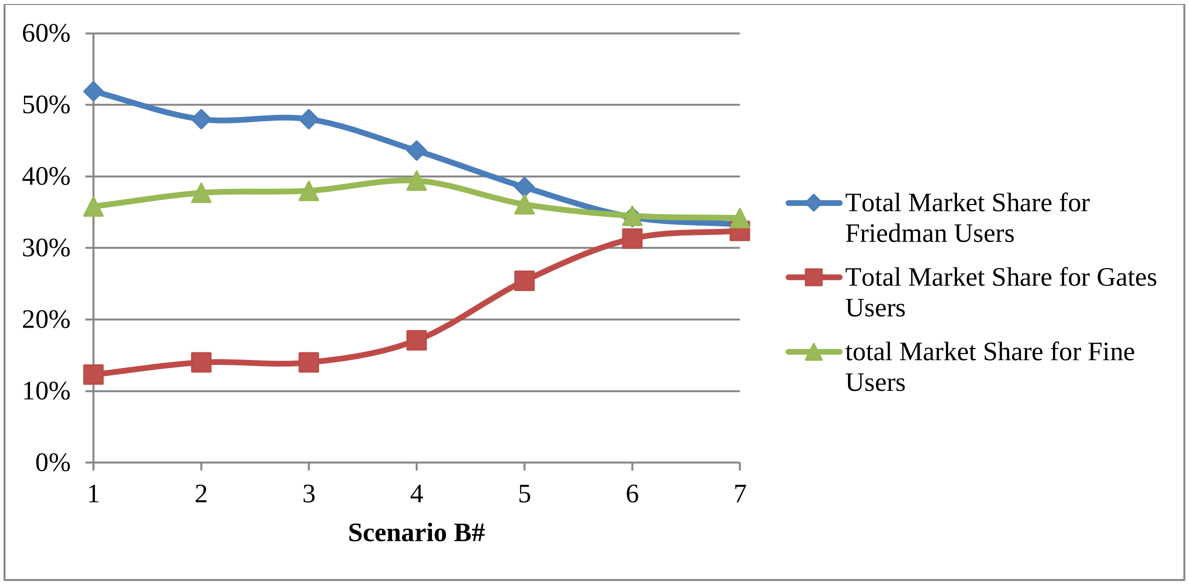


Figure 4.2. Market Share of Contractors in scenarios B1 to B7

The total value of the market in 10 years of the simulated time is almost the same in all scenarios. To better understand the impact of learning mechanisms, the sum of working capitals of the three contractors using each learning mechanism is calculated and considered in the analysis. For scenario B6 and B7, an adjustment is needed because there are cancelled projects so that the total profit comes from less number of projects. The first observation, which is aligned with the previous observation, is the increasing trend of adjusted profit of all contractors going from scenario B1 to scenario B7. The second observation on the following figure is the increase of Gates users' working capital. To understand this increase and the change in order of contractors in terms of working capitals, profit per project and market share should be considered. While contractors have converged to equal division of the market through scenario B1 to B7, Gates users were able to gain higher profit per project. This has resulted in a new order of contractors in terms of working capital: Gates users > Friedman users > Fine Users, as Figure 4.3 shows.

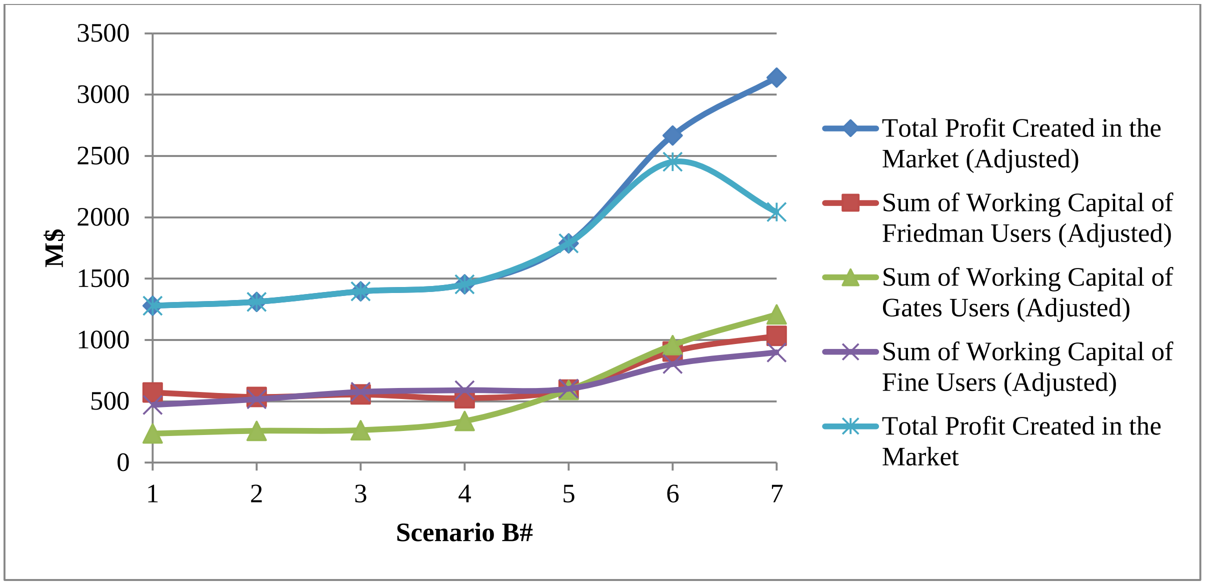


Figure 4.3. Working Capital of Contractors in Scenarios B1 to B7

4.4.3. Results of Experiment Set C

Table 4.13 and Table 4.14 present the results of all experiments in this sub-section. The main observation is that all Friedman, Gates, and Fine users have lost market share when uncertainty in cost estimation has increased. This suggests that the higher complexity and uncertainty of a project can enhance chance of an irrational contractor winning the project. Additionally, going from low to high uncertainty in cost estimation, the profit per project has increased for all Friedman, Gates, and Fine users. However, there is no consistent trend in terms of working capital; this is mainly because gaining higher profit per project is balanced off the loss in market share.

As Table 4.13 shows, Fine users have shown better performance in terms of market share when competing against irrational contractors compared to Friedman users. This is because Fine model only deals with the lowest bid-to-cost ratios while Friedman model considers the whole bid history of competitors. This is more obvious in scenario C1 where the uncertainty in cost estimation is low and markup can play a more important role; as a result, Fine users have chosen a very low markup (even less than Friedman users). By this choice, the Fine user has gained the lowest average profit per project not only compared to Friedman and Gates users but also compared to the irrational competitors in its experiment. Another interesting observation is that Gates model is not effective when competing against irrational competitors. The market shares that Gates users have gained in scenarios C1 and C2 are 16% and 14%, which are not considerably higher than the market share expected from an irrational, homogeneous contractor in a similar market (100% / 9 ≈11%).

Table 4.13. Performance of Friedman, Gates, and Fine Users in Scenarios C1 and C2

Learning Mechanism of the Contractor:	Friedman	Gates	Fine
Average Markup of the Contractor in Scenario #1	1.48%	2.79%	0.94%
Average Markup of the Contractor in Scenario #2	1.55%	3.62%	1.64%
Working Capital of the Contractor in Scenario #1 (M$)	477	329	515
Working Capital of the Contractor in Scenario #2 (M$)	513	369	509
Market Share of the Contractor in Scenario #1	33%	16%	38%
Market Share of the Contractor in Scenario #2	26%	14%	28%

Table 4.14. Profit per Project for All Contractors in Scenarios C1 and C2

Learning Mechanism of the Contractor:	Friedman	Gates	Fine
Average Profit per Project for the Contractor in the Scenario #1 (M$)	2.80	3.92	2.28
Average Profit per Project for Other Contractors in the Scenario #1 (M$)	2.46	2.62	2.34
Range of Profit per Project for Other Contractors in the Scenario #1 (M$)	[2.04, 2.62]	[2.53, 2.91]	[2.10, 2.69]
Average Profit per Project for the Contractor in the Scenario #2 (M$)	3.80	5.12	3.49
Average Profit per Project for Other Contractors in the Scenario #2 (M$)	3.58	4.07	3.78
Range of Profit per Project for Other Contractors in the Scenario #2 (M$)	[3.30, 3.88]	[3.72, 4.60]	[3.50, 4.20]

4.4.4. Results of Experiment Set D

Table 4.15 presents the results of scenarios D1 and D2. The order and trend in performance of contractors are consistent with the ones in scenarios A3 and A4 where Friedman users are more effective in gaining market share and working capital and Gates users are securing higher profit per project. Similar to experiment set C, Gates model does not perform effectively in terms of market share and working capital in mixed markets (markets that consist of both rational and irrational contractors). Another observation consistent with experiment set C is that irrational contractors have higher chance of securing contracts and profits in a market with more complex and cost-uncertain projects. However, in contrast to the results of experiment set C, Fine users are not outperforming others in terms of market share mainly due to existence of smart contractors that use learning mechanisms (Friedman and Gates users).

Table 4.15. Performance of All Contractors in Scenarios D1 and D2

Contractors	1 and 2	3 and 4	5 and 6	7 and 8
Learning Mechanism of the Contractors	Friedman	Gates	Fine	-
Average Markup of the Contractors in Scenario D1	0.67%	1.56%	0.93%	4.92%
Average Markup of the Contractors in Scenario D2	1.09%	2.76%	1.56%	5.08%
Working Capital of the Contractors in Scenario D1 (M$)	339	180	288	50
Working Capital of the Contractors in Scenario D2 (M$)	621	263	462	158
Average Profit per Project for the Contractors in the Scenario D1 (M$)	1.44	2.16	1.73	1.44
Average Profit per Project for the Contractors in the Scenario D2 (M$)	2.70	3.78	2.85	2.62
Market Share of the Contractors in Scenario D1	45%	16%	32%	7%
Market Share of the Contractors in Scenario D2	44%	13%	31%	12%

4.4.5. Results of Experiment Set E

Tables and figures in this subsection present different information and performance indicators of contractors and the market in scenarios E1 to E9. Trends and orders in these results are very consistent with the ones in the results of scenarios B1 to B7. As Table 4.16 shows, the average and minimum number of contractors in biddings has decreased from scenario E1 to scenario E9 due to imposing limitation of bonding capacity. This limitation has also caused cancelation of 85 and 219 projects under scenarios E1 and E9 (respectively) where contractors have reached their quota and were not able to participate in some of the biddings, resulted in the cancelation.

Table 4.16. Market information of scenarios E1 to E9

Scenario	E1	E2	E3	E4	E5	E6	E7	E8	E9
Maximum number of ongoing projects allowed	10	9	8	7	6	5	4	3	2
Average number of contractors participating in biddings	7.96	7.92	7.79	7.62	7.22	6.25	4.57	2.84	1.88
Minimum number of contractors participating in biddings	7	7	6	6	5	3	2	1	1
Number of cancelled project	0	0	0	0	0	0	0	85	219

As Table 4.17 shows the average markup of all contractors and volatility of the markup market have increased from scenario E1 to scenario E9. Submitted markup of Friedman and Gates users have increased partly due to the decrease in number of competitors in biddings. However, submitted markup of Fine users has been almost constant or has shown much less increase comparing to the ones of Friedman and Gates due to the fact that Fine model is non-sensitive to any specific contractor’s behavior and number of contractors participating in the bidding.

Table 4.17. Average markup of contractors and volatility of the market in scenarios E1 to E9

Scenario	E1	E2	E3	E4	E5	E6	E7	E8	E9
Average Markup of Friedman Users	1.10%	1.12%	1.07%	1.15%	1.20%	1.46%	2.18%	3.44%	5.10%
Average Markup of Gates Users	2.83%	2.72%	2.79%	2.81%	2.94%	2.95%	3.27%	5.40%	7.87%
Average Markup of Fine Users	1.59%	1.55%	1.60%	1.59%	1.52%	1.64%	1.67%	2.04%	1.84%
Average Markup of Random Users	5.04%	4.98%	5.19%	4.93%	5.02%	4.93%	4.85%	4.35%	4.41%
Average Markup of the Market	1.56%	1.51%	1.52%	1.51%	1.64%	1.93%	2.38%	2.86%	2.93%
One-Week Historical Volatility of Market Markup	1.08%	0.94%	0.95%	0.97%	1.07%	1.17%	1.55%	1.48%	1.82%
Annualized Historical Volatility of Market Markup	7.76%	6.80%	6.88%	7.00%	7.68%	8.43%	11.18%	10.64%	13.13%

According to Figure 4.4, Limiting number of projects a contractor can have has caused inflation in contractors' submitted markup and consequently their bids regardless of contractors' bidding methods. In other words, this limitation restricted the competition and lowered the market efficiency. One interesting observation is that with the increase in the limitation, Friedman users increasingly acquired higher profit per project compared to others and particularly they outperformed Fine users on this indicator under scenario E7, E8 and E9. The explanation for this new order of profit per project is the same mentioned in experiment set B.

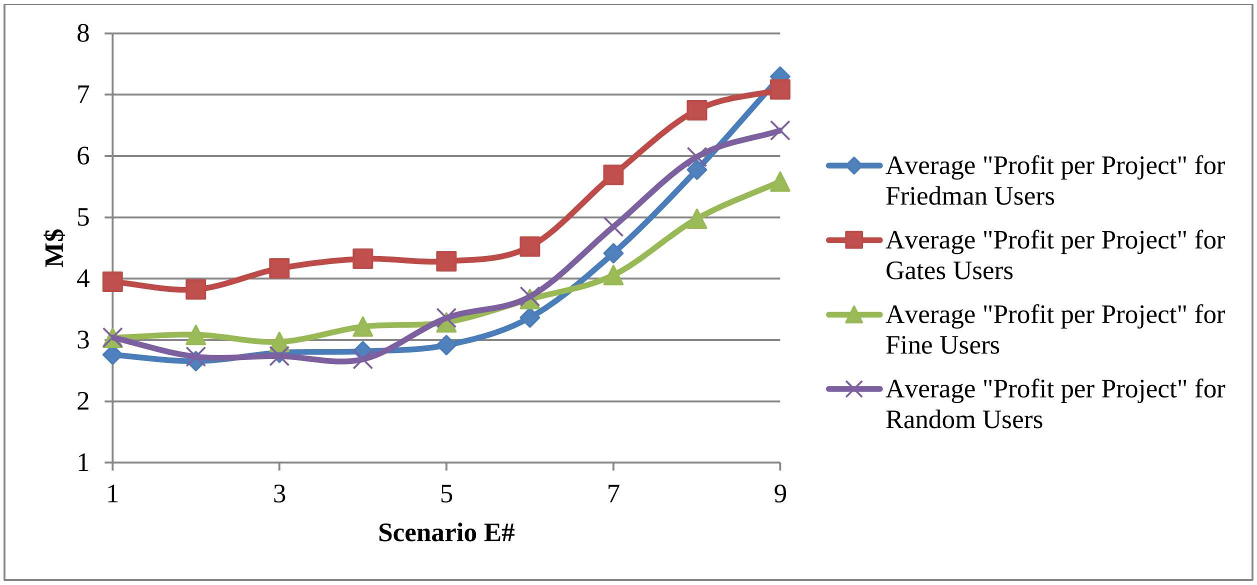


Figure 4.4. Profit per project of contractors in scenarios E1 to E9

Similar to experiment set B, imposing the limitation of bonding capacity has reduced market share of Friedman users. In scenario E9, the market is divided almost equally among all contractors as shown in Figure 4.5.

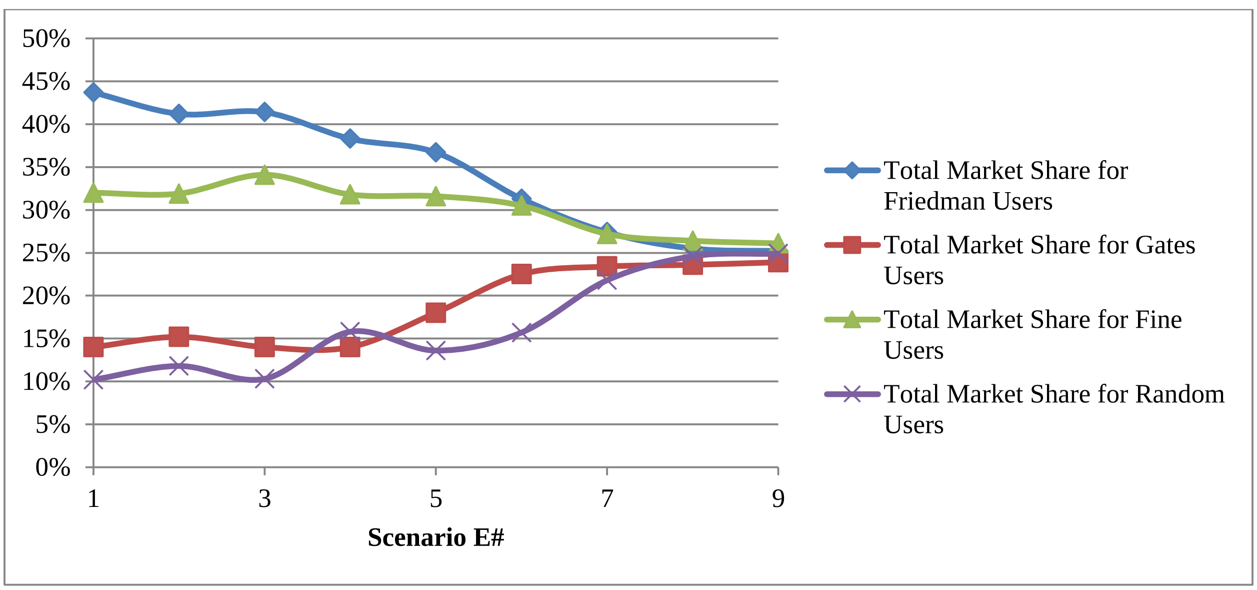


Figure 4.5. Market share of contractors in scenarios E1 to E9

In this experiment set, there are a number of cancelled projects under scenario E8 and E9. Therefore, the profits of all contractors should be adjusted by multiplying “520 / (520 – Number of Cancelled Projects)”. The first observation on Figure 4.6 is aligned with the previous observations in this subsection as well as in experiment set B; there exists an increasing trend of adjusted profit of all contractors going from scenario E1 to scenario E9. The second observation on the following figure is the increase of Gates users’ working capital. To understand this increase and the change in order of contractors in terms of working capitals, profit per project and market share should be considered. While contractors have converged to equal division of the market in scenario E9, Gates users also were able to gain higher profit per project. The third observation is the decline in working capital of Fine users in scenario E8 and E9 mainly due to lower profit per project.

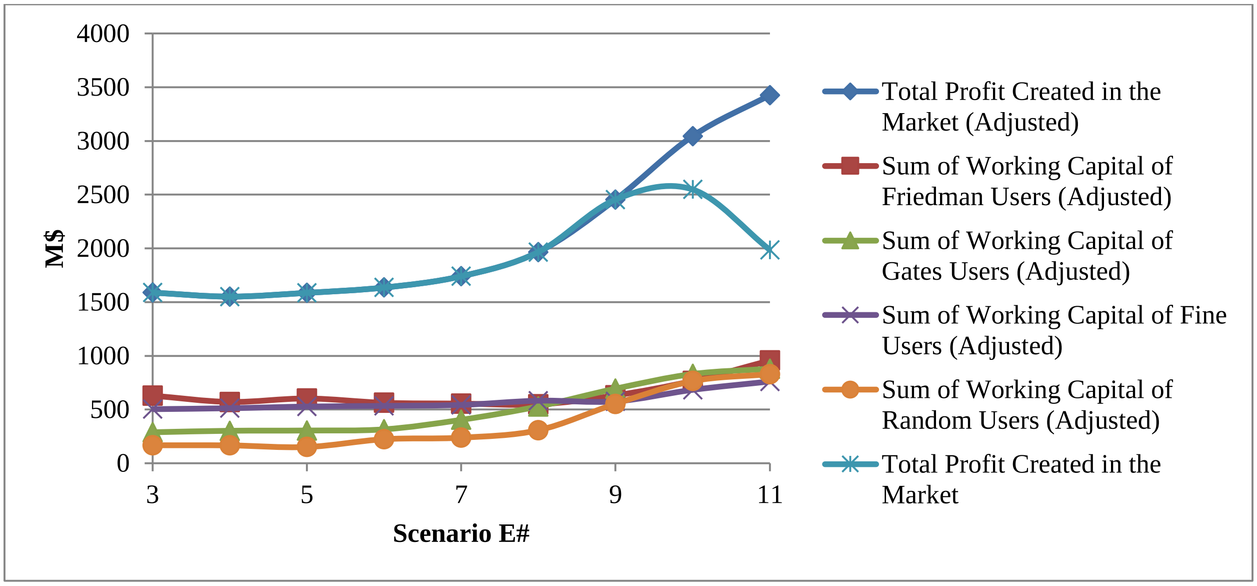


Figure 4.6. Working capital of contractors in scenarios E1 to E9

4.4.6. Results of Experiment Set F

Tables and figures in this subsection present different information and performance indicators of contractors and the market in scenarios F1 to F5. As Table 4.18 shows there are more cancelled projects in the market with the increase in minimum number of bid participants required from scenario F1 to F5. Also, both the average and volatility of market markup has decreased, indicating the fact that the requirement has made the market more competitive and efficient.

Table 4.18. Market information of scenarios F1 to F5

Scenario	F1	F2	F3	F4	F5
Minimum number of bid participants required	4	5	6	7	8
Number of cancelled projects	0	16	47	151	250
Average Markup of the Market	1.85%	1.77%	1.72%	1.65%	1.54%
One-Week Historical Volatility of Market Markup	1.16%	1.06%	1.08%	0.90%	0.84%
Annualized Historical Volatility of Market Markup	8.33%	7.62%	7.76%	6.49%	6.04%

As Figure 4.7 shows the average profit per project has decreased for all contractors going from scenario F1 to F5 mainly because of the more fierce competition. This also caused the change in order of contractors in terms of profit per project. In particular, random contractors have suffered higher drop in profit per project going towards more competitive scenarios.

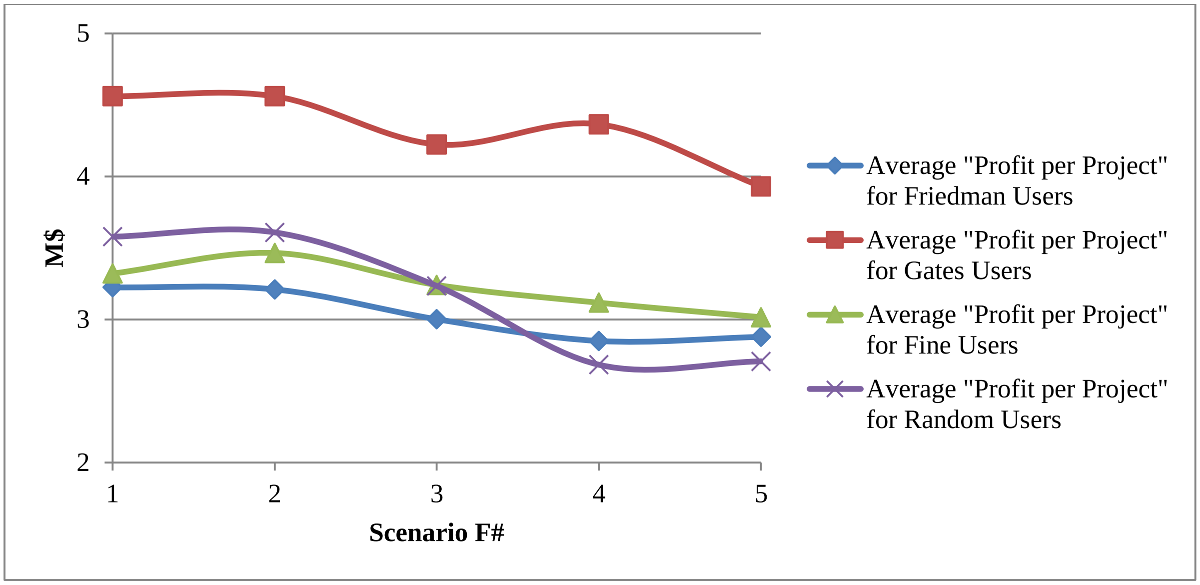


Figure 4.7. Profit per project of contractors in scenarios F1 to F5

Figure 4.8 shows a very interesting phenomenon, which is the divergence in allocation of market among contractors. More effective learning contractors are able to secure higher market share in more competitive market scenarios. This results in a bigger gap between more effective and less effective contractors.

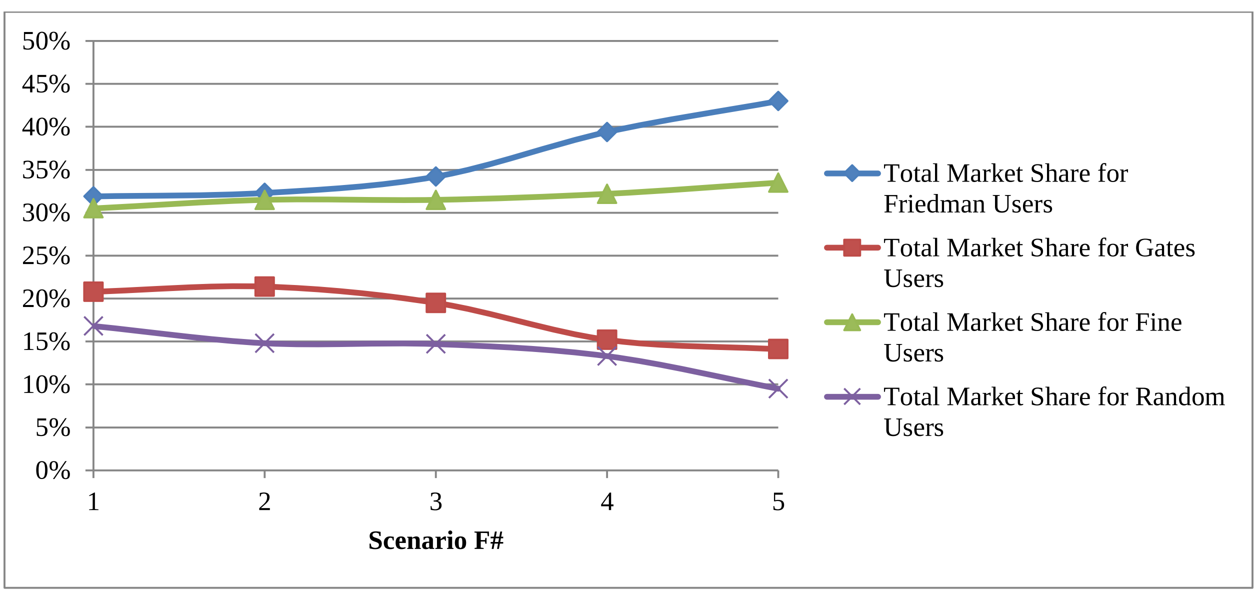


Figure 4.8. Market share of contractors in scenario F1 to F5

Due to the increase in competition going from scenario F1 to F5, total profit created in the market has decreased and the gap between more effective and less effective contractors has increased as shown in Figure 4.9. The main reason Friedman users were able to maintain/increase their working capital is the increase in their market share. This could balance off the decrease in their profit per project.

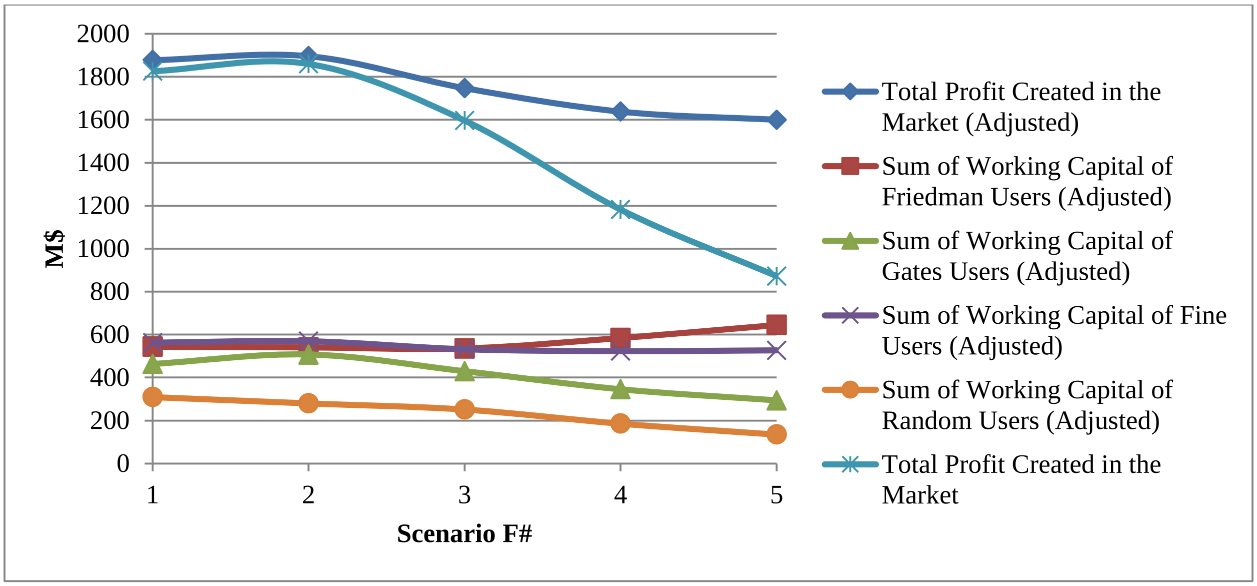


Figure 4.9. Working capital of contractors in scenarios F1 to F5

4.5. Chapter Summary

The controversial subject of competitive bidding in construction has attracted research, analysis, and surveys by both the construction academia and industry. However, the results of all investigations and debates have been insightful to some extent but not conclusive yet. This study attempted to introduce a new approach for evaluating the effectiveness of quantitative bidding methods in particular models introduced by Friedman and Gates. While the emphasis of the previous studies (Crowley, 2000; Fuerst, 1976; Ioannou, 1988; King & Mercer, 1985, 1987; Rosenshine, 1972; R. M. Skitmore, Pettitt, & McVinish, 2007; Stark, 1968) was on validity and reliability of those methods using mathematical arguments and retrospective approaches, this study put these methods in various scenarios to examine their applicability and effectiveness using a prospective approach, agent based modeling. The main research question in the literature was which of two models, Friedman or Gates, gives the correct probability of winning a competitive bid. For example, (Mitchell, 1977) tested both Friedman and Gates models and concluded Friedman model provides correct probabilities when there is no uncertainty involved in the cost estimates whereas Gates model provides correct winning probabilities when the distributions of both the contractor and its competitors have the same mean and variance. However, this chapter was more interested in answering which models can outperform others in a long run. The observations and results from the experiments conducted in this study were not limited to answering this question. It also shed lights on some characteristics of construction bidding environment raised from micro-behavior of its constituents: contractors and projects. The results offer new understandings and insights on quantitative bidding methods and recommendations for both owners and contractors' competitive success, which are not available using conventional approaches.

- Using Friedman model can result in considerably higher number of won projects (higher market share) whereas using Gates model can result in higher profit per project. This is because Gates model suggests relatively high probabilities of winning at high markups and does not encourage contractors to place low bid markups like Friedman model.

- In stable markets comprising rational competitors, the volatility in price of construction services can be due to uncertainty in cost estimation arising from factors such as the complexity of projects and incomplete contract specifications and information. Additionally, it can be concluded that inaccuracy and variance in cost estimation is one of the major factors in volatility of markup in the market.
- When market consists of heterogeneous contractors in terms of their markup decision model, there is larger variance in the market markup. However, when all contractors are using the same model (like using only Friedman model), the markup equilibrium had a very low variance over the time and was almost fixed.
- In all experiments, the profit margin of the winning contractors was less than 5% which is aligned with rate reported in the literature (AGC, 2000; Bashford, 1996; Leitch, 2000). It is worth mentioning that this rate is lower than the return of risk-free treasury bonds.
- One factor contributing to the higher variance in the market is varying set of contractors participating in biddings. This is important for a newcomer to understand about a market because such a variance in a market suggests that the competitors carefully research and learn about each other and they adjust their markup according to their competitors and not just solely on the level of market competition (which is what Fine model operates based on).
- Although Fine model has shown a good prospect specifically in competition against unpredictable contractors, the fact that it ignores bid history of specific competitors makes it unfavorable and unreliable in situations where market participants change regularly. A reliable learning mechanism considers bid history of competitors in biddings with varying participants. This is aligned with the conclusion by (Carr, 1983): contractors need to adjust

their markup from one project to the other depending on the change in the number or identity of competitors.

- Comparing results of experiment sets B and E, it can be concluded that the with the increase in number of rational, sophisticated contractors the benefits unpredictable contractors can get from higher uncertainty in cost estimating will decrease.
- Comparing those scenarios with low and high uncertainty in cost estimation (Scenarios C1, C2, D1, and D2) suggests that in many occasions choosing the optimal markup may not be what matters most. In other words, winning a contract is likely the combined outcome of a low markup and underestimation of the project value relative to the competitors. Therefore, when analyzing its performance and trying to find causes of success/failure in securing contracts in different markets, a contractor should consider characteristics, complexity, and cost uncertainty of projects.
- A good decision model should lead to correct decisions for the correct reasons. Each bidding decision model has its own strengths and weaknesses. The choice of a firm's bidding decision model for a specific project depends on many factors including the firm's business strategy, the project characteristics, and the client. The quantitative bidding methods explained in this chapter can be used as a decision support tool. If gaining higher market share in long-term, dominating a market and establishing relationship with clients are of high priorities for a contractor, Friedman model can suggest a better markup aligned with these goals.
- In markets where there is limitation on number of projects a contractor can secure and the bid preparation cost is insignificant (therefore contractors are able to bid on as many

projects as they want), the choice of bidding decision model is not a major distinguishing factor.

- Imposing the limitation of bonding capacity can make market less efficient; it decreases the gap between more effective and less effective contractors and increase average profit per project across the market.
- Requiring a specific number of bid participants will make the market more efficient, lower the average and volatility of market markup, decrease the average profit per project, increase the gap between market share of more effective and less effective contractors, and reduce the total profit created for contractors in the market.
- Comparing results of experiment sets B, E, and F shows the contrasting impacts of two different market limitations, namely limitation of bonding capacity and minimum number of bid participants required, on performance of contractors and the market.
- The results of the experiments in this study have implications for clients too. Clients who are interested in achieving the most efficient and cost effective bids should consider announcing their projects when there is enough number of qualified contractors. Sophisticated contractors take the number of competitors into account when choosing their markup; therefore, they have higher a chance for winning the contract. This results in lower markup and then lower total cost to clients.

CHAPTER 5. ANALYSIS OF INTERACTION AMONG COST ESTIMATING, MARKUP DETERMINATION, AND PROJECT EXECUTION AND THEIR IMPACT ON PERFORMANCE OF CONTRACTORS

“Scientific views end in awe and mystery, lost at the edge in uncertainty, but they appear to be so deep and so impressive that the theory that it is all arranged as a stage for God to watch man's struggle for good and evil seems inadequate”. ~ Richard P. Feynman

5.1. Introduction

Construction contractors are project-based organizations. Usually a department or unit in the organization called “Business Development & Marketing” is in charge for market research, establishing relationships with the clients, and identifying opportunities. After a prospective project is introduced to the organization, major decision/action phases in a contractor business model can be:

1. Bid/No Bid
2. Cost Estimating
3. Pricing (or Markup Determination)
4. Project Execution

Different departments/units in the organization are responsible for each of the above phases. In cost-based competition, all competing contractors have access to a large collection of drawings and specifications (L. Liu & Zhu, 2007). Based on those inputs, contractors first come up with an estimate of their costs for completing the project. Then, they add a markup, usually calculated as a percentage of the estimated cost, in order to cover profit and/or firm overhead (Hegazy & Moselhi, 1995). Figure 5.1 presents elements of construction project costs.

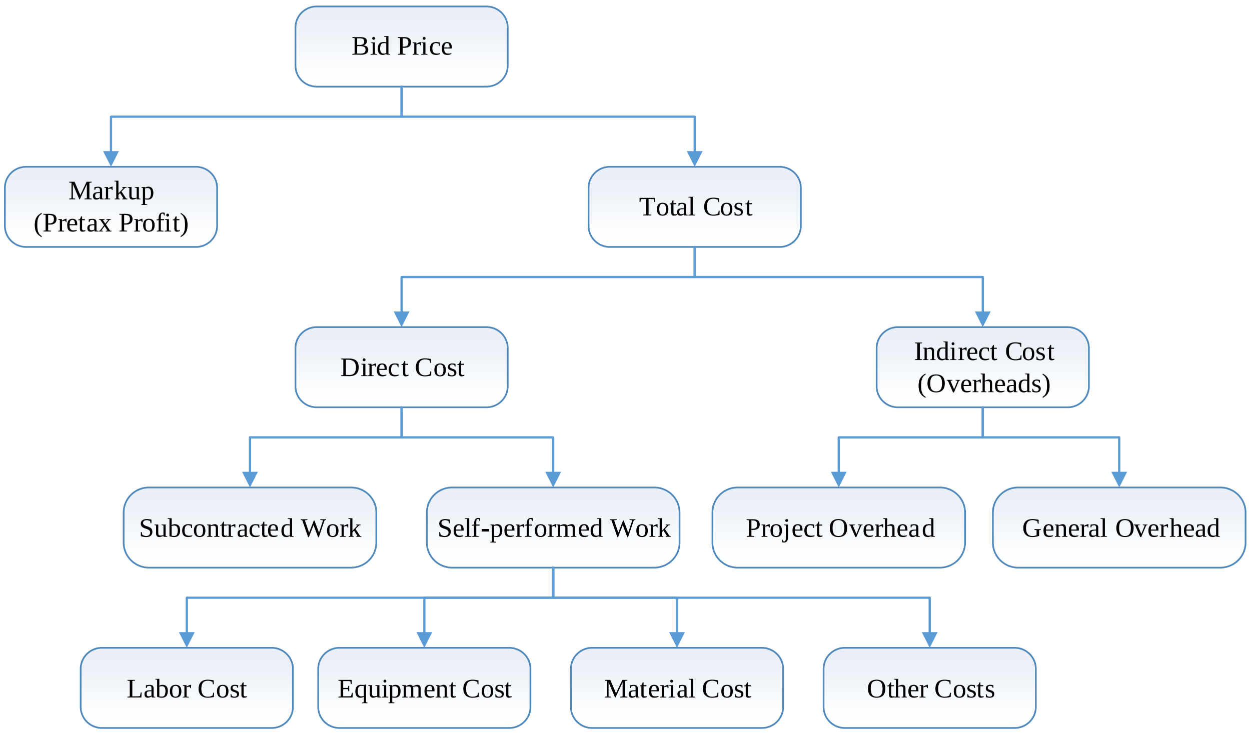


Figure 5.1. Components of construction project costs adapted from Yuan (2011)

Due to its vital importance to the business success of contractors, there is usually a separate department in the contractor organization for cost estimating. An estimate is a prediction and substitutes for an actual measurement that is not economical or possible (Harris & McCaffer, 2013). The aim of cost estimating is to provide information for a reliable bid decision-making. Therefore, in theory the cost that the estimating department produces is the most likely cost to the firm if they win the contract. While the general belief is that estimating is an experience-based process but technology and management systems can help estimators have a more accurate prediction.

Studying the literature suggests that contractors can improve their cost estimating accuracy using new technology or management systems.

One key organizational element involved in the bid preparation process is risk attitude. A construction project involves a variety of risks and uncertainties. According to the Project Management Institute's PMBOK, project risk is defined as an uncertain event or condition that, if it occurs, has a positive or negative effect on a project’s objectives. In this study, risk is defined as the possibility that the actual cost of a project will be higher than the estimated cost due to internal or external factors. Contractors need to consider project risks, uncertainties and complexities when deciding to bid on a project and determining the bid price. Contractor usually manage and mitigate risks through subcontracting some portions of their work, enhancing their cost estimating and management skills, tailoring contract conditions, sharing risks with other parties involved, and relying on claims after winning the project (Laryea & Hughes, 2010) because they want to limit inflating their bid prices and maintain their competitiveness. Nevertheless, there still remains some residual risk that cannot be, identified, predicted, and quantified even after applying all risk management strategies. A rich body of literature has been created on identification of risks at levels of construction projects and firms, current risk management practices in the industry, and strategies for improving risk management. However, the impact of risk attitude on bidding performance and its interaction with other bidding parameters have not been explored yet. This study is an attempt to address the following research questions using an agent-based approach:

1. How does the interaction among risk attitude, cost estimating accuracy and project management skills affect contractors’ performance in low and high risk markets?

2. Is there an optimal risk attitude by which contractors can improve their long-term performance?

Answering the above questions helps managers of construction firms understand the impact of their organizational culture on long-term performance of the firm. The approach taken in this study can be used for formulating and exploring impacts of an organizational element on a firm's performance in a competitive environment.

The organization of this chapter is as follows: The next section extensively reviews the literature on risk attitude, cost estimating, and actual cost of construction projects, in particular, in the bidding context. The "Methodology & Description of Experiments" section presents the main features of the simulation model and the features it adds to the virtual laboratory developed in Chapter 3. Then, this section describes the experiments to be conducted in this study. The "Results and Discussion" section presents and discusses main observations and results of the experiments. Finally, the "Conclusion" section summarizes the key insights and findings of the study.

5.2. Literature Review on Risk, Cost Estimating, and Actual Cost Determination

Generally, construction risks are defined as events that influence project objectives of cost, time and quality. The risk attitude of a contractor affects the way it perceives the inherent risk in a project and the impact it can have on the firm's decisions and strategies. There are several formal techniques practiced in the industry (Bing, Tiong, Fan, & Chew, 1999; Kartam & Kartam, 2001; Lyons & Skitmore, 2004; Smith & Bohn, 1999) as well as newly developed models for risk management that can enhance contractors' profit. For example, (Al-Bahar & Crandall, 1990) developed a systematic approach for identifying, analyzing, and managing project risks. A number of methods were developed specifically for managing various risks for international construction projects (Baloi & Price, 2003; Hastak & Shaked, 2000; Zhi, 1995). Conducting a survey of the top 100 large U.S. contractors, (Kangari, 1995) studied the current attitude of large U.S. construction firms toward risk and risk management practice, compared his survey results with a risk survey conducted by ASCE, and showed that contractors have been more ready to assume specific risks either partially or totally. Based on a questionnaire survey of general contractors to evaluate project management practices, (A. S. Akintoye & MacLeod, 1997) concluded that risk analysis and management depend largely on intuition, judgement and experience for many contractors.

Numerous studies in the literature studied current cost estimating practices in the industry or proposed new methodologies for improving cost estimating process for both owners and contractors. (A. Akintoye, 2000) conducted a comparative study of 84 UK contractors to identify the factors influencing contractors' cost estimating practice. (A. Akintoye & Fitzgerald, 2000) documented current cost estimating practices and identified main causes of inaccuracy in cost estimating through a questionnaire survey of UK contractors. In another study by (Ogunlana & Thorpe, 1991), factors affecting estimating accuracy were identified through opinion survey of eight offices and empirical data from 51 road construction projects. Analyzing data from 56 projects and from a postal questionnaire survey of 102 quantity-surveying firms, (Aibinu & Pasco, 2008) investigated key project characteristics influencing the accuracy of cost estimates and recommended strategies for improving the accuracy of estimates. (An, Kim, & Kang, 2007) proposed a case-based reasoning model that integrates experience from previous cases in all processes of construction cost estimating using the analytic hierarchy process. Integrating experiential learning theory with feedback and self-monitoring systems, (Lowe & Skitmore, 1994) proposed a mechanism to improve the accuracy of pre-tender estimates.

With respect to actual cost determination, there are many studies trying to identify key factors influencing the actual cost of projects. Interviewing 450 selected private residential project owners and developers in Kuwait, (Koushki, Al‐Rashid, & Kartam, 2005) identified contractor-related problems, material-related problems and, owners' financial constraints as the three main causes for cost overruns private residential projects and recommended strategies for mitigating their impacts. (Attalla & Hegazy, 2003), also, identified 36 factors that have direct impact on the cost performance of reconstruction projects through a survey of construction professionals and applied statistical analysis and artificial neural networks to develop models for forecasting cost deviation in reconstruction projects. (R. M. Skitmore & Ng, 2003) analyzed 93 Australian construction projects in order to develop a regression model for predicting the actual construction cost. Finally, studying 258 projects in 20 countries worth more than US$90 billion suggested that cost escalation in transport infrastructure projects is a global phenomenon (Flyvbjerg, Skamris Holm, & Buhl, 2003).

5.3. Methodology & Description of Experiments

As explained in the previous sections, this chapter is aims to study the interaction among key parameters involved in the processes of cost estimating, markup determination, and project execution. The main focus is on the impact of risk attitude on pricing and financial performance of contractors in the bidding environment. The methodology used in this investigation is agent-based modeling.

5.3.1. Simulation Model

The general attributes and characteristics of contractors and projects are based on the original template of the virtual laboratory developed in Chapter 3. Projects are generated sequentially over a simulation period of ten years. Time unit of the simulation is set to be equal to a week in reality. Experiments in all scenarios are repeated 100 times to ensure consistency in the results.

Specifically in this study, a contractor uses two functions when it comes to decision or action points. The function “costEstimation” samples the cost estimate of a contractor from a normal distribution with mean equal to the project’s estimated budget and a variance that is determined based on the contractor's estimation skills, previous similar experiences, the project's complexity, and completeness of the project documents.

In this chapter, a "markup" function is developed that combines utility theory and Friedman model (Friedman, 1956). Utility theory captures the risk attitude of contractors in the bidding process and Friedman model approximates the probability of winning of a contractor against its competitors. This combined model is aimed to find the optimal markup that maximizes profit utility of a contractor instead of its profit value.

Because of the uncertainty in the actual cost, a contractor is facing a lottery with different outcomes given winning the project. In utility theory, a certainty equivalent value, $CE[V]$, is the value at which the an individual is indifferent between receiving or facing the risk of the profit lottery, *V*. In other words, the utility of certainty equivalent is equal to the expected utility of the lottery. Translating this concept to the bidding context, the certainty equivalent value is the value a risk-averse contractor would require to take on a risky project. The concept of certainty equivalent helps replacing the set of uncertain profit lottery outcomes with its certainty equivalent value. Therefore, a contractor is solving the following optimization problem that is trying maximize the product of the probability of winning against opponents given a certain markup *x* and *n* opponents and the utility of the certain equivalent ($CE[V]$) of the corresponding profit lottery:

$$\max E[U(V)|\, x,n] \;=\max Probability(Winning|\, x,n) \,\times\, U[CE(V)] \qquad (5.1)$$

To have the closed-form expression of $CE[V]$, it is assumed that a profit utility function is exponential and the profit outcomes follow a normal distribution. As shown in the following equation, an exponential utility function is used that depends solely on one parameter that is the contractor's risk aversion coefficient, γ:

$$U(V) \;=\; 1 -\; e^{-\gamma V} \qquad (5.2)$$

Where V is the expected profit realized in a certain project and $U(V)$ is the profit utility.

Risk aversion coefficient, γ, represents risk behavior of contractors. The higher this coefficient is, the more risk averse a contractor will be in the process of markup determination. The risk aversion coefficient can be different from one contractor to another. Considering these two assumptions, $CE[V]$ can be determined using the following equation (Clemen and Reilly 2014):

$$CE[V] = M_V - 0.5\,\gamma . V_V \qquad (5.3)$$

Where M_V and V_V are the mean and variance of the expected profit realized at project completion, respectively. These two variables depend on the actual cost of the project, which will be realized at the end of the project. For this study, the actual cost is assumed to follow a normal distribution with the mean set at the estimated cost of the project as determined by the contractor's function "costEstimation" and the variance chosen according to the project complexity level as perceived by the contractor. The following equation summarizes a contractor's optimization problem in the simulation:

$$\max Probability(Winning|\, x, n) \,.\, (1 - e^{-\gamma\,((x-1)\,M_V - 0.5\,\gamma . V_V))}) \qquad (5.4)$$

To serve the educational purpose of this dissertation, the algorithm and actual codes (in Java) of the function "markup" used in this chapter are provided in the appendices section of the dissertation. This equation helps integrate internal and external parameters involved in cost estimating, markup decision, project complexity, and actual cost. The following figure shows an abstract representation of the interaction among these parameters.

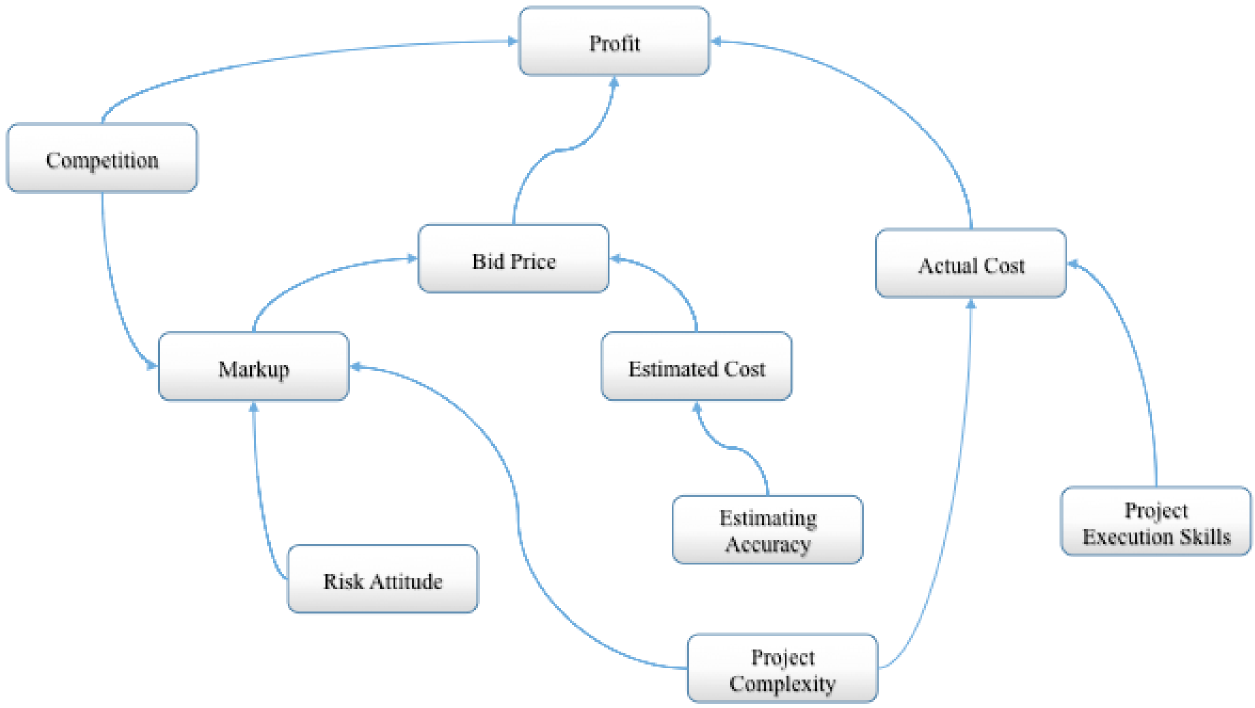


Figure 5.2. An abstract representation of the interaction among key parameters in bidding

5.3.2. Description of Experiments

This section describes the purpose and details of experiments conducted in this chapter. Under scenario A1 to A6, ten contractors have exactly the same initial attributes including bonding capacity, firm size, work specialty, working capital, workload limit, cost estimating accuracy and project execution capability, but different attitudes towards risk. Contractor 1 and Contractor 10 are assigned the lowest and highest risk-aversion coefficients, respectively. All projects are created of the same type matching the already set specialty for all contractors. Table 5.1 presents the conditions adopted for each scenario in the experiment set A. For example, the first scenario assigns poor cost estimation and project management skills to all contractors at the start of the simulation and defines a low complexity for all generated projects. The conditions under the second scenario are the same as the former one but with all projects having a high complexity level.

The purpose of the first four scenarios is to analyze the interaction among cost estimating accuracy, level of uncertainty of projects, contractors' risk attitude, and project management skills and assess their impact on performance of contractors and the market. The optimal markup decision of contractors, their financial performance over time and the markup market are among outputs of interest. Comparing scenario A1 and A2 with A3 and A4 helps investigate the sensitivity of the markup decision made by contractors with varying risk attitude to high uncertainty in project cost estimation and to low/high project risk levels.

Scenario A5 and A6 are trying to replicate a more realistic version of construction markets where there is a mix of projects with low to high complexity levels. The purpose of scenarios A5 and A6 is to find the level of risk attitude that optimizes a contractor's financial success in a long run.

Table 5.1. Characteristics of projects and contractors under scenarios A1 to A6

Scenario	Project Complexity	Cost Estimating Accuracy and Project Execution Skills of Contractors
A1	Low	Normal
A2	Low	Improved
A3	High	Normal
A4	High	Improved
A5	Mixed	Normal
A6	Mixed	Improved

5.4. Results

This section presents and discusses the results that were obtained in six experiments described in the previous section. As Figure 5.3 and Figure 5.4 show, market share and total working capital created in the market under scenario A1 and A2 are almost evenly distributed among all contractors since their standard deviations are insignificant. The almost equal allocation of market share and working capital is mainly due to low level of project complexity that results in lower variance between the actual cost and the estimated cost. The small variance among contractors' working capital in different runs can be attributed to the normal level of cost estimating accuracy and project execution skills. This variance is less in Scenario A2 because of the improved level of cost estimating accuracy and project execution skills. However, the distribution of market share is slightly skewed towards slightly risk averse contractors while the distribution of working capital is slightly skewed towards extremely risk averse contractors.

Observing the working capital of scenario A1 and A2 suggests that when level of project uncertainty and complexity is low, risk attitude has an insignificant impact on contractor's performance and it does not separate the slightly, moderately, and extremely risk averse contractors from each other. In addition, comparing the results of scenario A1 with scenario A2 suggests that improving cost estimating accuracy and project execution skills causes a considerable increase in contractors' working capital (total profit) although the average market markup has decreased by almost 33% (which is (3.3%-2.21% / 3.3%)) as shown in Table 5.2. This table also shows that as the contractor's risk aversion coefficient increases, its optimal markup increases for almost every tendered project over the simulated five years.

Comparing performance of contractors in markets with low risk projects (scenarios A1 and A2) with markets with high risk projects (scenarios A3 and A4) suggests that as the project uncertainty and inherent risk increases, the risk attitude of the contractor exerts a higher impact on its optimal markup decision. Another interesting observation on this comparison is the considerable increase in working capital of all contractors and higher dispersion of market share among contractors.

Comparing the results of scenario A3 with scenario A4 suggests that improving cost estimating accuracy and project execution skills causes a considerable increase in contractors' working capital of most contractors. The only exception is the decline in working capital of extremely risk averse contractors in markets with high-risk projects compared to their working capital in markets with low-risk projects due to the considerable drop in their market share.

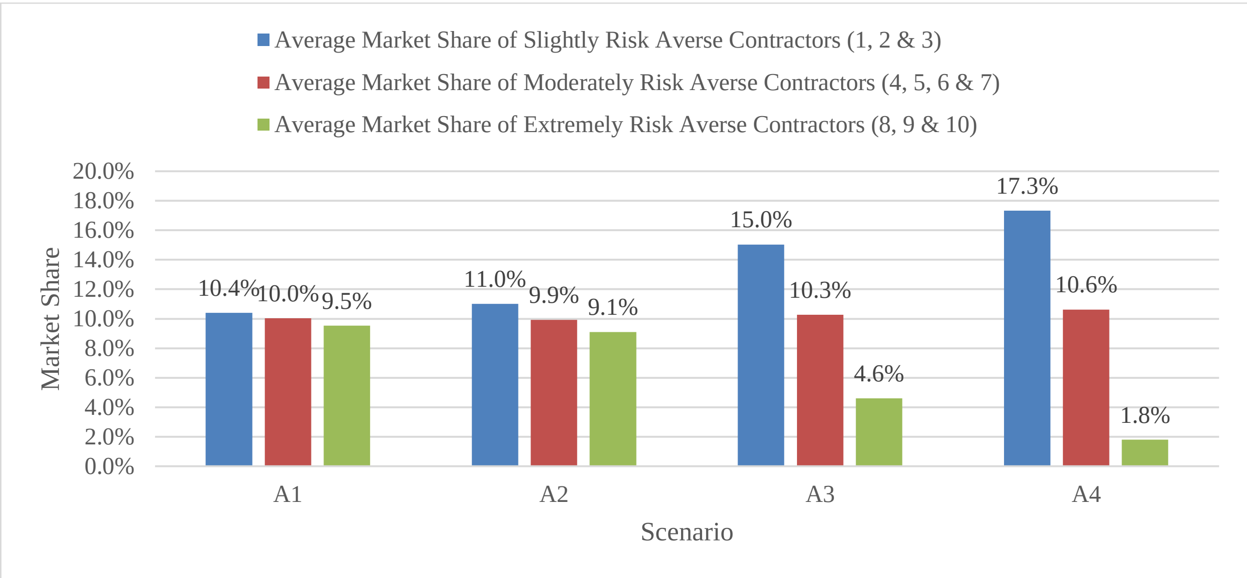


Figure 5.3. Market share of contractors under **scenarios A1-A4**

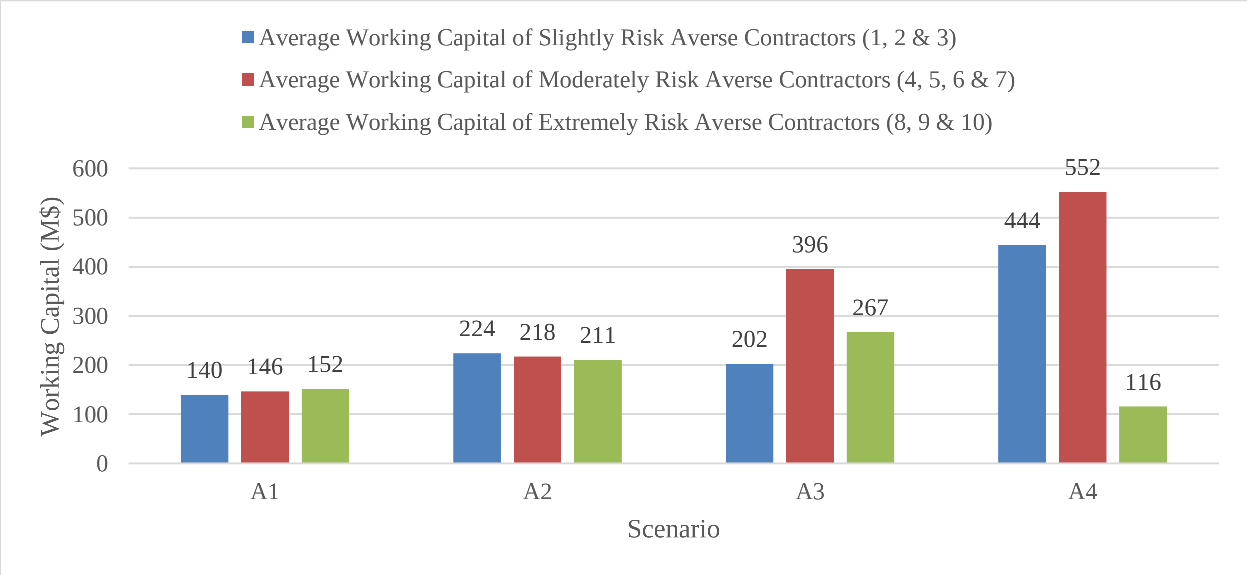


Figure 5.4. Working capital of contractors under s**cenarios A1-A4**

Table 5.2. Average markup of contractors under scenarios A1-A4

	Scenario			
	A1	**A2**	**A3**	**A4**
Average Markup of Slightly Risk Averse Contractors (1, 2 & 3)	2.99%	1.84%	13.27%	12.61%
Average Markup of Moderately Risk Averse Contractors (4, 5, 6 & 7)	3.51%	2.35%	21.53%	20.36%
Average Markup of Extremely Risk Averse Contractors (8, 9 & 10)	3.79%	2.87%	30.12%	29.04%
Average Market Markup	3.30%	2.21%	16.79%	15.79%

Figure **5.5** presents the market share of contractors for scenarios A5 and A6. The first observation is the fact that risk attitude has direct impact on market share. The less risk averse a contractor acts when bidding, the higher share of the market they can secure in a long run. In other words, slightly risk averse contractors have obtained larger market share in both scenarios. The main reason for this order of market share distribution is the impact of risk attitude on markup determination. The second observation is the considerable impact of improving cost estimating accuracy and project execution skills on the market share of contractors. With this improvement, slightly risk averse contractors increased their market share compared to the scenario under which all contractors have normal cost estimating accuracy and project execution skills. Under scenario 2, moderately risk averse contractors have almost managed to keep their market shares in scenario 1. However extremely risk averse contractors have lost around 25% (which is (7.3% - 5.5%) / 7.3%).

Figure **5.6** presents the working capital of contractors, which is the accumulated gross profit over the simulation period. Moderately risk averse contractors have outperformed others in both scenarios A5 and A6 although they have not obtained the highest market shares in the market. This is mainly due to the facts that moderately risk averse contractors have better adjusted their markup so that they can make more profit per project compared to slightly risk averse contractors and that they can have much higher market share compared to extremely risk averse contractors. Another important observation is the change in order of contractors' financial performance from scenario A5 to scenario A6. Under scenario A5, the extremely risk averse contractors have been more successful than slightly risk averse contractors. However, this is not the case under scenario A6. The slightly risk averse contractors have gained more working capital compared to the extremely risk averse contractors. This suggests that a contractor can take more risk when determining the markup if its cost estimating accuracy and project execution skills are well improved.

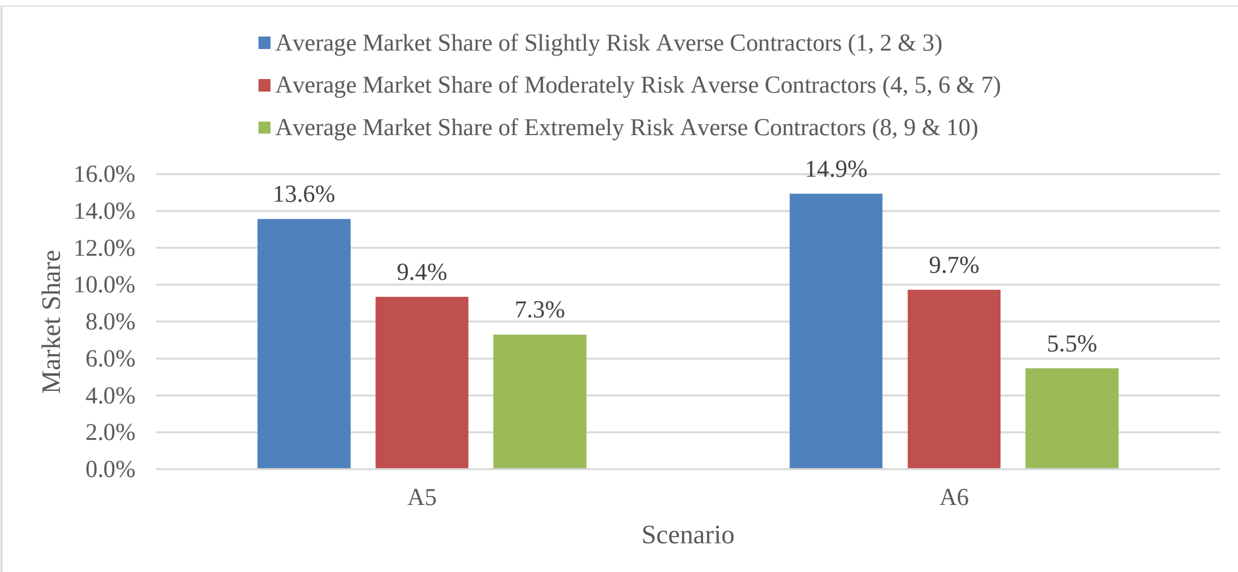


Figure 5.5. Market share distribution under scenarios A5 & A6

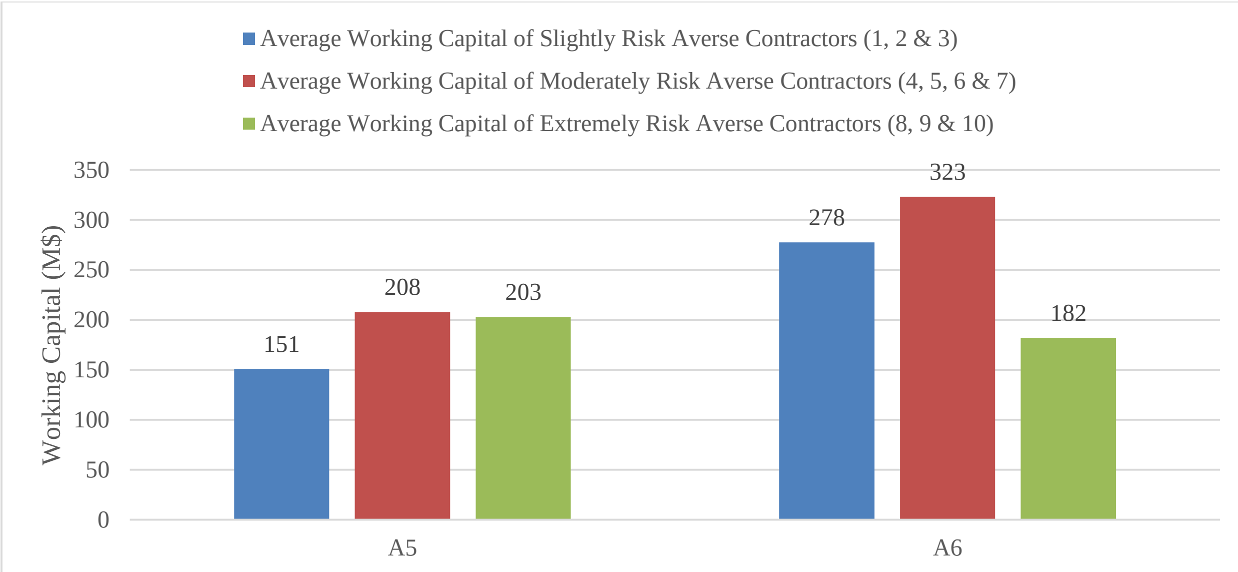


Figure 5.6. Working capital under scenarios A5 & A6

5.5. Chapter Summary

In this chapter, six simulation experiments were designed and conducted to study the effect of contractors' risk behavior, cost estimating and project management skills, and complexity of projects on contractors' choice of optimal markup, long-term financial growth and market share. The results of this study show:

- There is a significant impact of a contractor's risk behavior on its optimal markup and this impact is most in markets where projects are of high complexity and uncertainty. In other words, when project complexity is low, the markup is usually hardly influenced by risk attitude.
- This study shows that moderately risk averse contractors can financially outperform others in a long run. Also, the comparative performance of slightly and extremely risk averse contractors depends on level of cost estimating accuracy and project execution skills of contractors. This hypothesis was also confirmed in a study conducted by (Kim &

Reinschmidt, 2010, 2011) which used Monte Carlo simulation to model the decision of bid/no bid for contractors with varying risk attitude and concluded that risk tolerant contractors tend to bid more often and at lower prices than risk averse ones.

- The contractor's good financial performance and market survival depends on his own characteristics, the market conditions and projects' attributes. In particular, risk attitude in markets with medium to high risk projects has considerable impact on contractors' survival and financial status. Results strongly suggests that moderately risk averse contractors tend to perform better and generate more profit than other contractors. Also, results indicate a better accuracy in the cost estimation of projects and more controlled management of the construction process generate higher profits for most contractors even when their markups decrease.
- The inherent risk level of a project is at the core of the markup decision and may result in significant inflation of bid prices in the market. All conducted experiments showed an average observed increase of 10 percent in markups moving from low to high risk projects for a given scenario with all other parameters being equal. This matches the 5-10 % margin for risk allowance in bids confirmed in the review study conducted by (Laryea & Hughes, 2010) about analytical risk models and actual contractors' risk allocation practices.

CHAPTER 6. ANALYSIS OF INTERACTION AMONG COMPETITION, RISK, AND WORK CONTINUITY IN A DESCRIPTIVE BIDDING METHOD

"Human beings, viewed as behaving systems, are quite simple. The apparent complexity of our behavior over time is largely a reflection of the complexity of the environment in which we find ourselves." ~ Herbert Simon

6.1. Introduction

Descriptive (positive) and prescriptive (normative) decision theories are two schools of thought in decision sciences. Descriptive decision models mainly explain how decision is made whereas prescriptive decision models recommend how a decision should be made (Bazerman & Moore, 2012). According to Simon's Nobel Prize winning works (March & Simon, 1958; Simon, 1965) decision making can be better understood by describing and explaining actual decisions, rather than by focusing solely on prescriptive decision analysis. In the previous chapters, profit was the only objective a contractor was trying to maximize in the simulation and prescriptive decision models such as models introduced by (Friedman, 1956) and (Gates, 1967) were used in the markup function of agent contractors. Although profit maximization in a competitive context is recognized as the most frequently used bidding objective (Boughton, 1987), many researchers argue that it is not always and should not be considered the sole criterion in markup decision making process. There are several deductive studies in the construction bidding literature that reveal the underlying factors characterizing the bidding decision making behavior of contractors through conducting questionnaire surveys and interviews. Findings of those deductive studies can be used to build a descriptive decision model that replicates decision-making behavior of a typical contractor in the construction competitive bidding. With identifying major decision criteria in construction bidding for a typical contractor, behavioral rules of agents can be defined in a simple and reasonable manner (Metcalfe & Foster, 2007). The significance of agent-based modeling is in its ability to capture the complexity that arises from the interaction of agents even-though their behaviors seem simple. This study aims to understand the interaction among major markup components and their influence on the contractors' performance. In particular, two main objectives of this chapter are:

1. observing the impact of a contractor's risk attitude on his markup decision taking into account its need for work and the market competition,
2. assessing if and to what extent considering need for work in the markup decision affects the financial growth of a contractor and its market share.

To address these questions, this chapter is organized as follows: The "Background" section reviews main works in the literature of construction bidding that have taken a descriptive approach through the study. Using findings of those studies, a multi-attribute markup decision model is conceptualized and developed. The "Methodology & Description of Experiments" section describes implementation of the multi-attribute markup decision model as the markup function of contractors in the virtual laboratory. Then, several simulation experiments are conducted to address research questions outlined in the "Introduction" section. The "Results and Discussion" section presents results of the experiments and discuss major observations. Finally, the "Conclusion and Future Works" section summarizes key findings and insights and outlines directions for future research in this area.

6.2. Literature Review on Descriptive Studies of Construction Biddings

As explained in Chapter 3, the literature of construction bidding can be classified into three categories based on the methodological approaches: Induction, deduction, and simulation. The following table presents major deductive studies in the literature. All these studies that aimed to identify key factors that contractors consider when making bidding decisions stressed the multi-attribute nature of markup decision making and the fact that a contractor's internal conditions (including need for work, risk behavior, current workload, financial capacity, firm size and others) are equally and sometimes even more important than project attributes and market characteristics. To define the behavioral rules, this chapter focuses on three of the most influential bidding factors identified in the literature namely, the market competition, the risk behavior and the need for work. This choice is supported by the literature. (Ahmad & Minkarah, 1988; Chua & Li, 2000; Shash, 1993) identified need for work was as one of the most influential factor in making a contractor take any measures to win the job. Based on their internal characteristics, organizational culture, and risk attitude, contractors have varying perceptions about market conditions and projects' uncertainties (Oo et al., 2010). At the time of bidding, a construction project can be seen as a lottery with different profit outcomes and with a level of uncertainty resulting from the expected variance in the final cost of the project. Depending on their risk attitudes, the value of this lottery and its appeal varies from one contractor to another. In an empirical study, (de Neufville & King, 1991) showed that each of the two components, risk and need for work, causes independently and additively a rough increase of 3% in the bid price of a contracting firm. Besides competition, risk, and work continuity, there are some other less important factors affecting the optimal markup decision identified in the literature such as type of project and inherent complexity, client character and record of payment, reliability of subcontractors, and degree of uncertainty in cost estimates.

While the former studies identified the major markup defining components, they failed to consider and discuss the interaction among them and the relative dominance of one on the other within a market of heterogeneous contractors exhibiting different bidding behavior and strategies. This study aims to address this gap.

Table 6.1. Review of Major Descriptive Studies in the Literature Construction Bidding

Author(s)/Year	Description of the study	Contribution of the study
Ahmad and Minkara (1988)	A survey for identifying main factors for US contractors when making bid/no bid and markup decisions	Need for work, type of job, degree of hazard, economic conditions, competition, degree of uncertainty in cost estimate, and reliability of subcontractors are key factors in determining the markup.
DeNeufville and King (1991)	An empirical investigation on the bidding decisions of 30 selected contractors in Boston, USA	Risk and need for work were identified as two influential factors in a contractor's bidding behavior. Different profit markup utility functions were developed for different possible combinations of these two factors.
Shash (1993)	A survey to find the most significant factors influencing the markup decision for 85 top UK contractors	Degree of difficulty, risk involved, current workload and need for work were identified are the most influential factors.
Hegazy and Moselhi (1995)	A survey condocted among 78 general contractors in Canada and the US to identify key factors influencing a contractor' bidding decisions	23 factors were grouped into four categories: 1- job uncertainty (owner attitude and project location), 2- job complexity (project size and the level of technology needed), 3- market condition (economic growth and expected competition), and 4- the firm's ability and need for work (expertise in similar projects and how desperately the work was needed).
Chua and Li (2000)	Interviews with competitive bidding experts and top contractors in Singapore for identifying key considerations in bidding decisions	The potential level of competition, the inherent project risk, the contract type, the company's bidding position and its need for the job are key factors.
Dulaimi and Shan (2002)	A survey to find factors that medium and large size contractors in Singapore consider when making their bid markup decision	40 factors were identified and classified into project characteristics, company's attributes, bidding situation, economic environment, and project documentation.

Ye et al. (2013)	A survey to find key factors contractors in China consider when determining bid prices for public projects	Major factors were identified, ranked, and classified into different categories including construction cost, contractor heterogeneity, payment terms, potential competitors, client requirements, market conditions, and third-party stakeholders.

6.3. Methodology & Description of Experiments

Similar to the experiments in the previous chapters, two main classes of objects are Projects and Contractors. Projects are generated sequentially over a simulation period of ten years and are assigned a set of characteristics such as the project budget chosen uniformly over the range [$80M, $120M], the project duration also selected uniformly between 20 and 30 weeks, the project complexity (low or high), and its actual cost based on the inherent uncertainty. On the other hand, a set of contractors is created in the market along with their attributes including their attitude towards risk, expertise, cost estimation skills, bidding competitiveness, financial status, work backlog and need for work, in addition to their decision making rules with respect to bidding on projects and markup choice. It is assumed that all contractors can estimate a project cost with the same level of accuracy and have the same level of management capability and expertise although there are uncertainties over the actual cost at which a project is completed given different level of project complexities. Note that the actual cost is set to follow a triangular distribution with a mean equal to the project's market budget. Figure 1 shows a schematic representation of the bidding process simulation and reflects the interaction among the different agents over time within one competitive environment. It is worth noting that the agent–environment boundary represents the limit of the agent's absolute control, not of its knowledge.

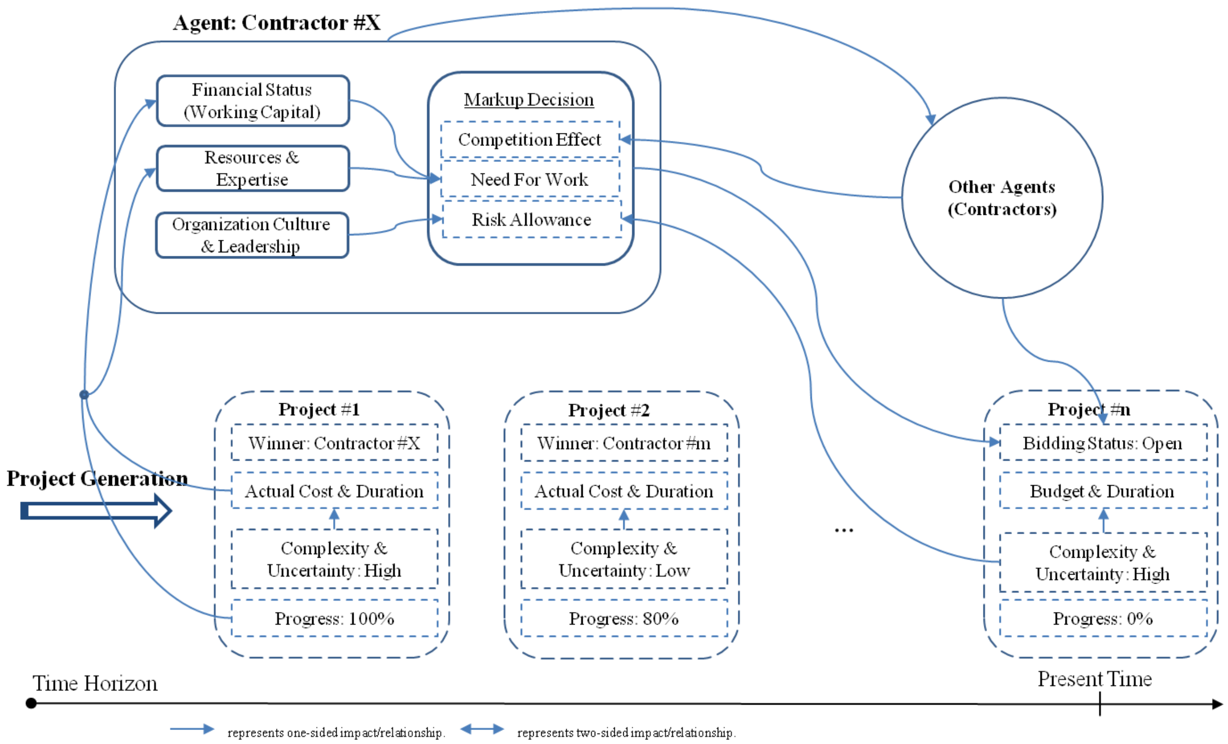


Figure 6.1. An abstraction of a contractor in the bidding environment and the network structure of the market

6.3.1. Multi-Attribute Markup Function

This study assumes that a typical contractor considers three independent criteria when trying to determine the markup for a certain project, which are the market competition, the inherent risk, and the need for work. Based on the descriptive studies in the literature, and to maintain behavioral rules simple and rule of thumb-like, an additive markup function was developed in this study consisting of three components described in the following subsections:

6.3.1.1. Competition Component

Competition has been identified as one of the main decision criteria for construction contractors when determining their bid price for a project (Hegazy & Moselhi, 1995; Smith & Bohn, 1999). To increase their chance of winning a contract, a contractor needs to adjust its markup with respect to the quality and quantity of competition demonstrated by their competitors (Carr, 1983). Bid competitiveness ratio expression introduced by (Oo et al., 2010) is used in this study to measure competitors' competitiveness.

$$BCR_{ip} = \frac{B_{ip} - B_{lp}}{B_{lp}} \qquad (6.1)$$

Where BCR_{ip} is the bid competitiveness ratio for opponent i on project p, B_{ip} is the bid price submitted by opponent i for project p, and B_{lp} is the lowest submitted bid for project p. This ratio calculates the gap between an opponent's bid and the lowest bid submitted for a project divided by the lowest bid. This ratio reflects how close a competitor's bid was to the lowest bid for a previous project and therefore the smaller this ratio is, the more competitive a competitor is. During each bidding cycle, a contractor determines the average bid competitiveness ratios for his potential opponents over the last ten projects tendered in the market using the following code excerpt from the developed model:

```
//This piece of code shows how the BCRip of each contractor i is computed and archived after determining the winning bid for every past project p//

for (Contractor c : get_Main().allContractors)
        {
        c.bidCompetitivenessRatio = (c.bidPrice / winningPrice) - 1 ;
        c.bidCompetitivenessDataset.add(this.projectID,c.bidCompetitivenessRatio);
        }

//This piece of code shows how the average BCRip over the last ten projects, named bidCompetitivenessTen, is computed for each potential opponent i on the current project p//

for (Contractor c : Opponents)
        {
        sum=0;
        for(int n = 0; n < c.bidCompetitivenessDataset.size() ; n++)
        {sum += c.bidCompetitivenessDataset.getY(n);}
        c.bidCompetitivenessTen = sum / c.bidCompetitivenessDataset.size();
        }
```

Then, once the average bid competitiveness ratios of potential opponents are determined, the contractor will be able to compare and rank himself among his competitors and hence evaluate the percentage of opponents who have been more competitive than him in the recent past projects. The lower this percentage is, the higher markup a contractor can afford to use in his bid price for the current project and thus the higher the competition component will be assigned in the developed additive markup function.

At the time of bid preparation, each contractor considers the past ten projects tendered in the market, determines the corresponding average competitiveness ratios for potential competitors and decides on the competition component of its markup value accordingly. The reason for limiting to just the past ten project is to consider the most recent behavior of competitors rather than their whole bid history.

6.3.1.2. Risk Component

As explained in the previous chapter, one key organizational element involved in the bid preparation process is risk attitude. Contractors consider a risk allowance in the bid price that is usually added to the markup as a percentage of total cost. The range for residual risk allowance percentage in bids is in the order of [0-3] % which is also adopted in this simulation (de Neufville & King, 1991; Laryea & Hughes, 2010; Smith & Bohn, 1999). The risk attitude of a contractor affects the way it perceives the inherent risk in a project and the impact it can have on the firm's bid price. In this chapter, there are three types of contractors with respect to risk attitude (Slightly Risk Averse, Moderately Risk Averse, Extremely Risk Averse) and two degrees of project risk (low and high) which are the main two factors defining the risk allowance component in the markup function:

```
if (riskAversion == mild)
        {
        if (project.riskLevel == low)
        riskcontingency = 0.00;
        if (project.riskLevel == high)
        riskcontingency = 0.01;
```

```
        }
else if (riskAversion == moderate)
        {
        if (project.riskLevel == low)
        riskcontingency = 0.01;
        if (project.riskLevel == high)
        riskcontingency = 0.02;
        }
else  (riskAversion == extreme)
        {
        if (project.riskLevel == low)
        riskcontingency = 0.02;
        if (project.riskLevel == high)
        riskcontingency = 0.03;
        }
```

6.3.1.3. Need for Work Component

Contractors need to maintain a certain work backlog so that they can cover their general and administrative costs and retain skilled personnel. In this simulation, the parameter Work-in-Progress Limit is defined as the average annual workload a contractor can have during a year given its size and capabilities. Accordingly, the need for work ratio (NWR) for a contractor i is determined through the following equation:

$$NWR_i = 1 - \left(\frac{Current\ Work\ Volume}{Work - in - Progress\ Limit}\right) \quad (6.2)$$

The closer this ratio is to 1, the higher the need for work and the lower the markup is expected to be; and the closer this ratio is to 0, the lower is the contractor's need for work and the higher markup it can afford. Through surveying contractors in the market, (de Neufville & King, 1991) showed that a high need for work could roughly decrease the bid price by 3%. The need for work component in this study is selected within the range [0-4] % and its specific value is chosen based on two variables namely the financial status of the contractor and the previously defined need for work ratio. The financial situation of a contractor is assessed through the positive or negative change to its initial working capital.

6.3.2. Description of the Experiments

This subsection explains the details of three sets of simulation experiments conducted in this study. Nine contractors are defined in the market and are set to have the same value for initial working capital, work limit, cost estimation and project management skills. Each contractor can simultaneously work on four projects at most. Given the number of contractors in the market and their work limit, the market is considered very competitive in all sets of experiments. Each experiment set has been run for 100 times in order to ensure the consistency of the results. Table 6.2 presents a summary of the experiments sets and their purposes.

The purpose of the first set of experiments (A) is to examine what level of risk attitude results in the contractor's best financial performance on the long run. The result will be compared with findings in the literature in order to check and verify capability of the simulation model. There are nine contractors competing with each other in the market including three slightly risk averse contractors, three moderately risk averse contractors, and three extremely risk averse contractors. Table 6.3 shows the risk attitude assigned for each of the nine contractors. In the first set of experiments, projects are generated in the market one at a time unit under three different scenarios. Under scenario A.1, all projects have low level of complexity and uncertainty. Under scenario A.2, the market comprises a mix of projects with low and high level of complexity and uncertainty. In this case, always the next project has high (or low) level of complexity and uncertainty with a probability of 50%. As for scenario A.3, all projects have high level of complexity and uncertainty. These three scenarios are considered only in the first set of experiments in order to analyze the impact of project uncertainties on the results.

Table 6.2. Summary of the experiment set A, B, and C

Experiment Set	Purpose	Experiment Conditions
A	Finding the optimal level of risk attitude for contractors	Scenario 1: the market comprises only projects with low level of complexity. Scenario 2: the market comprises a mix of projects with low and high level of complexity. Scenario 3: the market comprises only projects with high level of complexity.
B	Finding whether considering "Need for Work" impacts business success of contractors	The market comprises a mix of projects with low and high level of complexity. All contractors are moderately risk averse.
C	Finding to what degree a markup discount should be considered to account for need for work	The market comprises a mix of projects with low and high level of complexity. All contractors are moderately risk averse.

The second set of simulation experiments (B) investigates the importance of the component "Need for Work". It aims at assessing whether considering "Need for Work" impacts business success of contractors on the long-term or not. If the answer is yes, the purpose of the third set of simulation experiments (C) is to find to what degree a markup discount should be considered to account for need for work.

In experiment set B, there are two types of contractors with ten contractors in total. As Table 6.3 shows there are five contractors who do not consider "Need for Work" and five other contractors who consider it and accordingly discount their markup up to 2%. Financial performance of the two sets of contractors is observed and compared in order to evaluate the effect of considering "Need for Work" in markup decision.

In experiment set C, there are five types of contractors with ten contractors in total, and these five types differ by the discount level at which they take the component "Need for Work" into consideration when determining their markup. Table 6.3 shows the varying levels of "Need for

Work" consideration in the markup function of the ten defined contractors. It is worth mentioning that the second and third sets of experiments were conducted under three levels of risk attitude separately in order to ensure that results are consistent regardless of the risk attitude of contractors. Also, the market consisted of a mix of low and high risk projects (similar to the scenario A2 under the first set of experiments) in both sets.

Table 6.3. Contractors' characteristics in the experiment set A, B, and C

Contractor	Risk Attitude in the experiment set A	Need For Work in the experiment set B	Need For Work in the experiment set C
#1	Slightly Risk Averse	Ignored	Ignored
#2	Slightly Risk Averse	Ignored	Ignored
#3	Slightly Risk Averse	Ignored	Discounted up to 1%
#4	Moderately Risk Averse	Ignored	Discounted up to 1%
#5	Moderately Risk Averse	Ignored	Discounted up to 2%
#6	Moderately Risk Averse	Discounted up to 2%	Discounted up to 2%
#7	Extremely Risk Averse	Discounted up to 2%	Discounted up to 3%
#8	Extremely Risk Averse	Discounted up to 2%	Discounted up to 3%
#9	Extremely Risk Averse	Discounted up to 2%	Discounted up to 4%
#10	N.A.	Discounted up to 2%	Discounted up to 4%

6.4. Results

This section presents and discusses the results that were obtained in the three sets of experiments described in the previous section.

6.4.1. Results of Experiment Set A

Table 6.4, Table 6.5, Figures 6.2 to 6.5 present the results obtained for the first experiment set. To be more specific, Figures 6.2 to 6.4 show the progress of the average working capital for the three levels of risk aversion versus the project ID under the three different described scenarios which exhibit varying degrees of project risk. As shown in each of these figures, moderately risk averse contractors financially outperform others in highly competitive markets in the long run. This result is consistent across all scenarios and is aligned with the result obtained in the literature and in

Chapter 5 of this dissertation (Kim & Reinschmidt, 2010, 2011). Also, slightly risk averse outperform extremely risk averse contractors in all scenarios. One of the methods for validating simulation models is comparing obtained results with real-world observations or findings from literature. In this case, results of this experiment set can be considered as a validation tool of the simulation model.

Comparing Figures 6.2, 6.3, and 6.4, it is observed that slightly risk averse contractors can do better in riskier markets. Slightly risk averse contractors, on average, have the highest difference with moderately risk averse contractors in terms of working capital when the market comprises low risk projects (Scenario A1). This difference decreases when moving from low risk to high risk market; namely, from scenario A1 to scenario A2 and then scenario A3. This can be due to the fact that when facing high uncertainty in projects, the more risk averse a contractor is, the higher the allocated contingency (risk allowance) in his bid which reduces his competitiveness. This gives a winning edge to slightly risk averse contractors over moderate ones, and thus the gap between the growing working capitals for both decreases from scenario A1 to scenario A3. Another observation about Figures 6.2, 6.3, and 6.4 is that, given a certain risk aversion level, the generated working capital representing an accumulation of actual project profits over time has increased from low to high risk market because all contractors will consider higher risk allowance in their markup to hedge against high level of risk in projects.

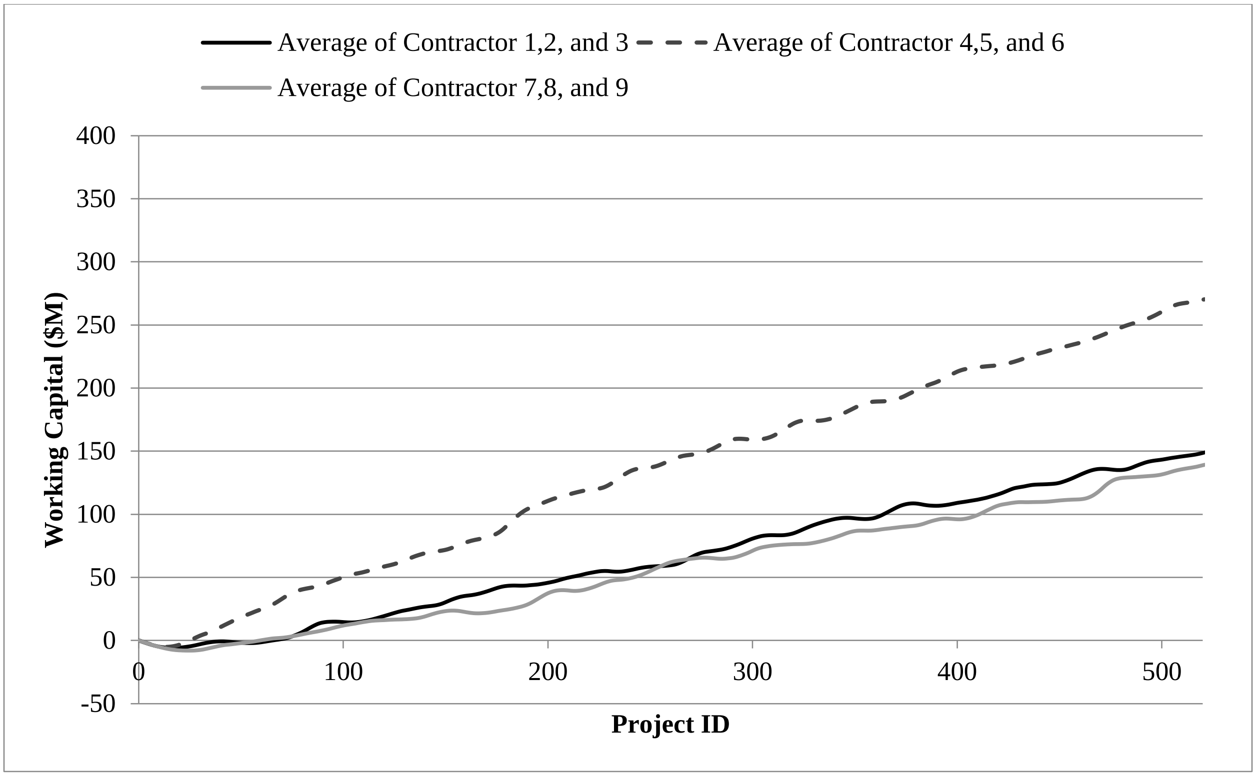


Figure 6.2. Financial performance of contractors in the experiment set A under scenario A1

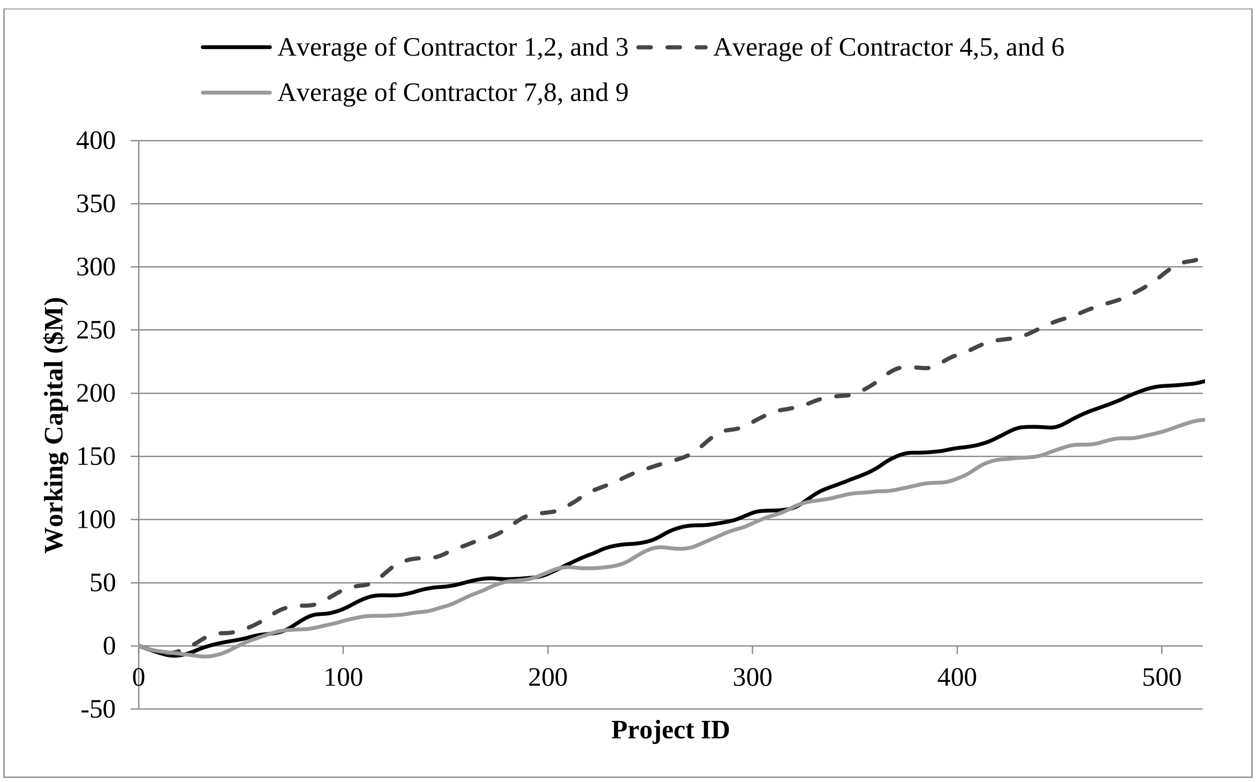


Figure 6.3. Financial performance of contractors in the experiment set A under scenario A2

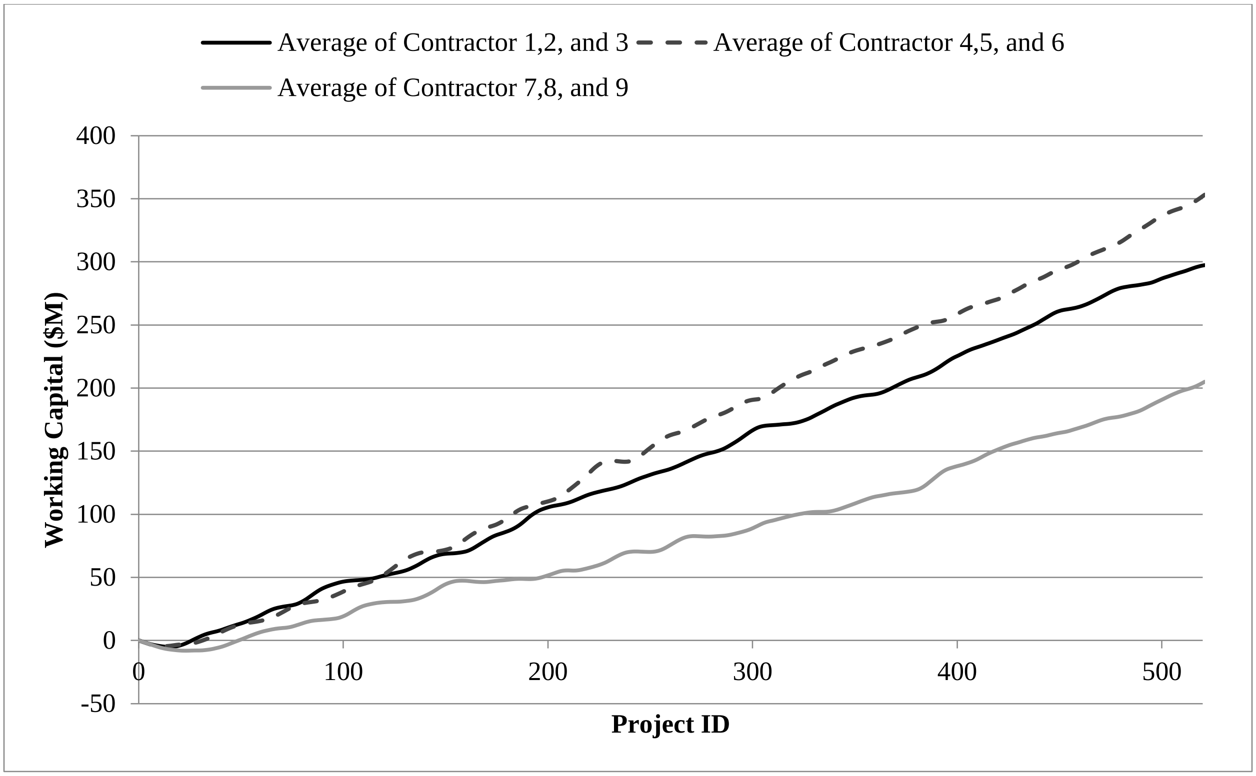


Figure 6.4. Financial performance of contractors in the experiment set A under scenario A3

Table 6.4 presents the working capital of contractors in the three scenarios. It also compares each contractor's performance with the best performance in the market in terms of working capital. As Table 6.4 suggests, the average working capital of contractors have increased from Scenario 1 to 3. In other words, in riskier markets, contractors increased their markup to cover the risk and thus could manage a higher profit. It is also observed that moderate risk averse contractors had the smallest average gap (Δ%) with the best performer in the market in all scenarios which again indicates that moderation in risk attitude is the optimal strategy regardless of the project risk level. Note contractors #5 and #6 exhibited the best financial performance in all three scenarios (Δ=0%). Another important observation that was emphasized earlier is that slightly risk averse contractors performed significantly better under scenario 3 where the average Δ% dropped from -41% in scenario 2 to -24% in scenario 3.

Table 6.4. Contractors' working capital in the experiment set A under scenarios A1, A2, and A3

	Working Capital ($M)					
	Scenario A1	Δ% with the best performance	Scenario A2	Δ% with the best performance	Scenario A3	Δ% with the best performance
Contractor 1	237	-25%	170	-54%	294	-28%
Contractor 2	90	-72%	292	-22%	299	-27%
Contractor 3	155	-51%	198	-47%	345	-16%
Average of Contractor 1, 2, 3	161	-49%	220	-41%	313	-24%
Contractor 4	260	-18%	346	-7%	321	-21%
Contractor 5	<u>318</u>	0%	271	-27%	382	-6%
Contractor 6	269	-15%	<u>372</u>	0%	<u>408</u>	0%
Average of Contractor 4, 5, 6	283	-11%	330	-11%	371	-9%
Contractor 7	163	-49%	207	-44%	202	-50%
Contractor 8	167	-47%	158	-58%	234	-43%
Contractor 9	112	-65%	194	-48%	224	-45%
Average of Contractor 7, 8, 9	147	-54%	186	-50%	220	-46%

Table 6.5 presents market share of the nine contractors under the three different scenarios. Please note that the market share of each contractor is defined to be the number of won projects over the number of tendered projects in the market:

$$Market\ share\ _i = \frac{\#\ of\ won\ projects\ by\ i}{\#\ of\ tendered\ projects\ in\ the\ market} * 100 \qquad (6.3)$$

This table supports again the conclusion that moderately risk averse contractors, on average, have a better performance under all market scenarios through having the highest share of projects among the three types of contractors.

Table 6.5. Contractors' market share in the experiment set A under scenarios A1, A2, and A3

	Market Share		
	Scenario A1	Scenario A2	Scenario A3
Contractor 1	12.3%	10.6%	10.9%
Contractor 2	9.0%	11.9%	10.9%
Contractor 3	10.9%	10.9%	12.3%
Average of Contractor 1, 2, 3	10.7%	11.1%	11.4%
Contractor 4	12.9%	12.3%	11.9%
Contractor 5	13.1%	12.1%	13.1%
Contractor 6	12.9%	13.4%	12.3%
Average of Contractor 4, 5, 6	13.0%	12.6%	12.4%
Contractor 7	9.6%	9.8%	9.6%
Contractor 8	10.2%	9.2%	9.4%
Contractor 9	9.0%	9.6%	9.4%
Average of Contractor 7, 8, 9	9.6%	9.5%	9.5%

Figure 6.5 shows the success rate of contractors throughout the simulation period. The success rate of a contractor is defined to be the number of won projects over the total number of projects the contractor has bid on:

$$Success\ rate_i = \frac{\text{\# of won projects by } i}{total\ \#\ of\ projects\ i\ has\ bid\ on} \qquad (6.4)$$

This figure confirms that moderately risk averse contractors, on average, outperform other contractors. Moreover, it show that contractors tend to converge to a somehow constant success rate after 2-3 years (in the simulation time scale). It is worth noting that the result in Figure 6.5 is from several simulation runs of experiment set A under scenario A2.

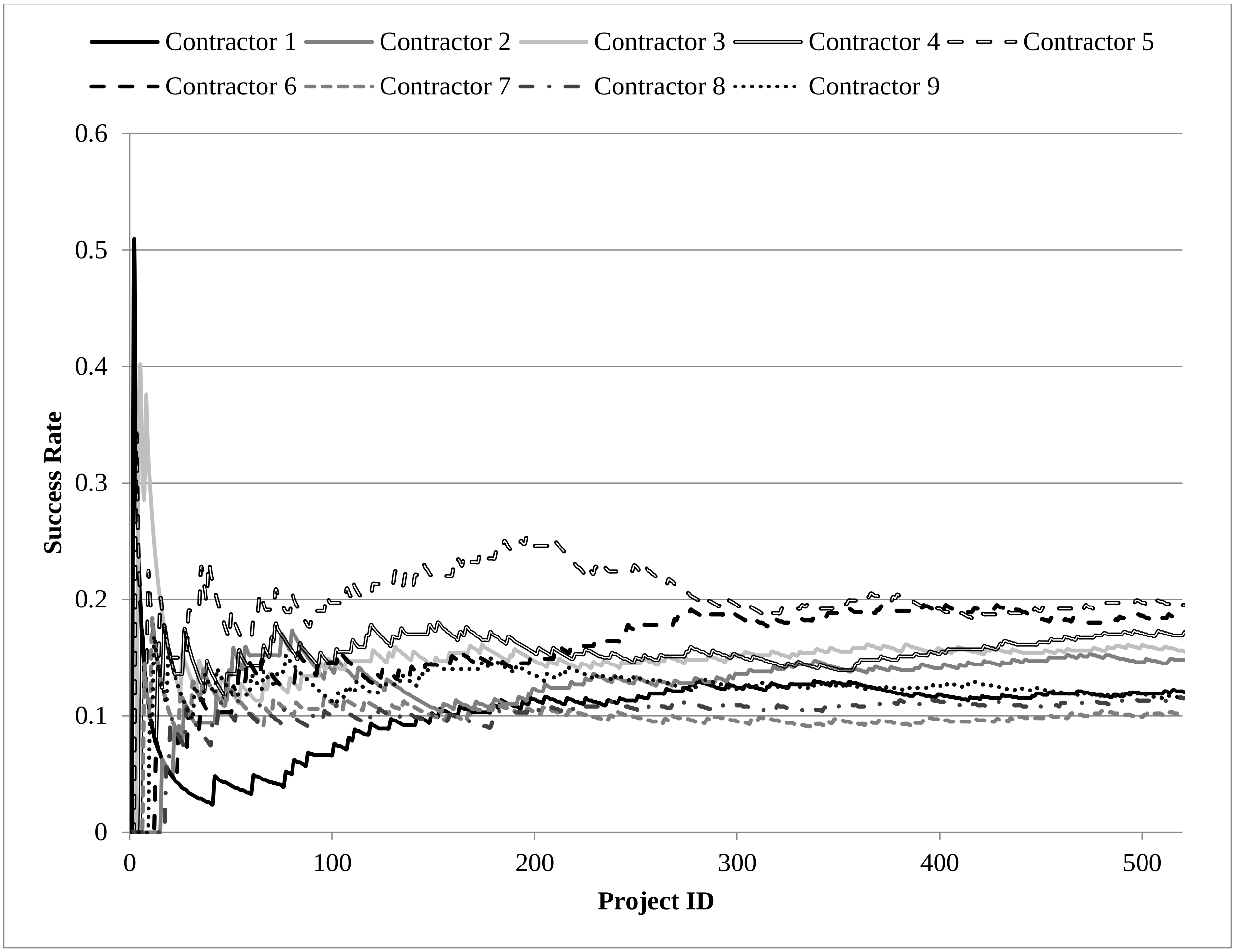


Figure 6.5. Contractors' success rate under scenario A2

6.4.2. Results of Experiment Set B

The results of the second set of experiments, as reflected in Figure 6.6, show that contractors 6, 7, 8, 9 and 10 who considered "Need For Work" as one of the criteria for determining their markup have a better financial performance compared to the contractors who did not (1, 2, 3, 4, and 5). This is because these contractors lower their markup strategically depending on their need for work and financial situation, which allows them to, possibly, acquire new projects when they have their resources idle, even though it might come at the expense of a lower expected profit. Specifically, this flexibility is of more help to contractors when risk level of projects is low and market competition is intense. It is worth noting that this experiment set is conducted with the same risk aversion degree for all contractors in order to isolate the “Need for Work” effect on contractors’ growing capital. Figure 6.6 shows the results obtained for moderate risk aversion level, however, the simulation was repeated another two times, once with mild risk aversion condition for all contractors and the other with extreme risk attitude. Both scenarios showed similar results.

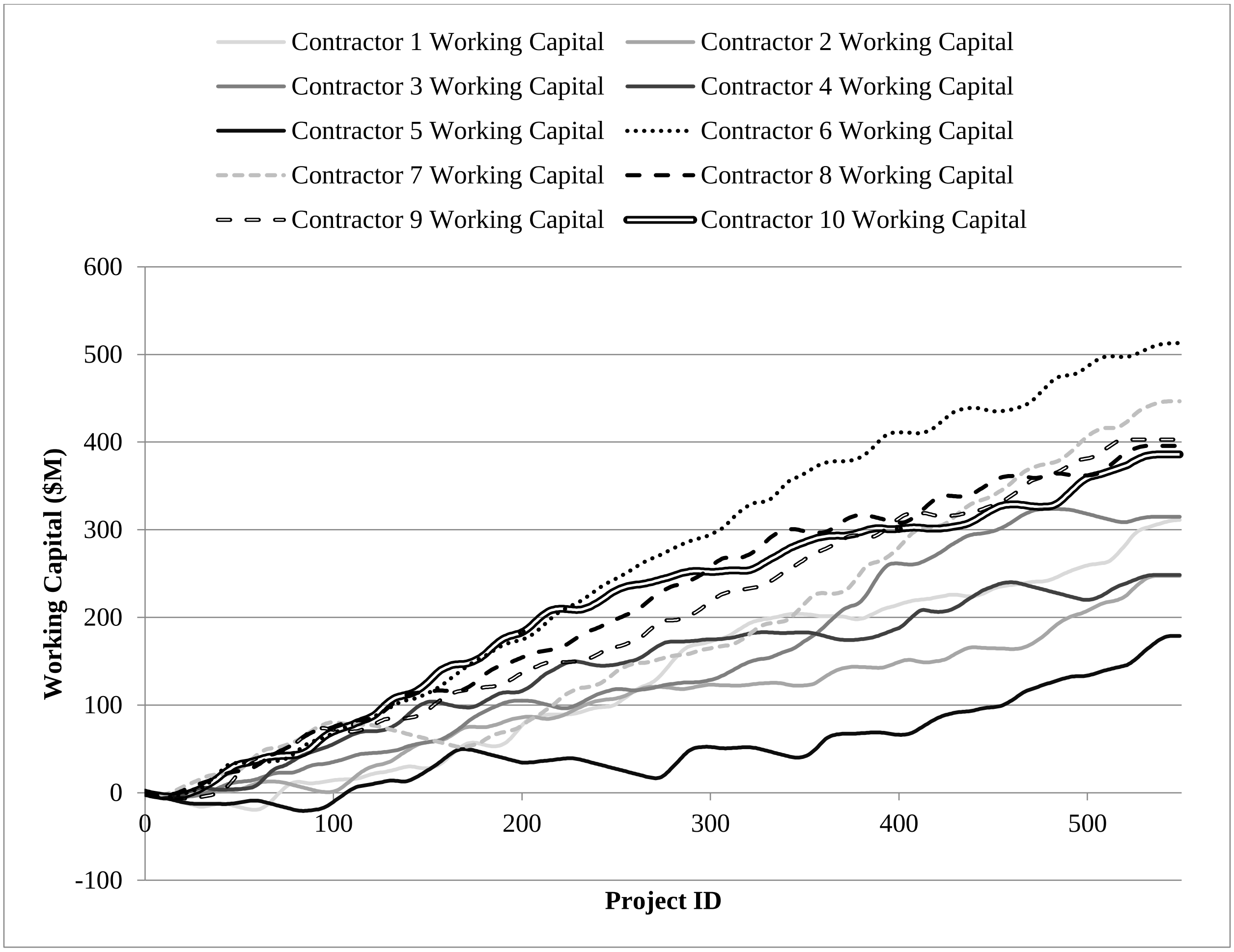


Figure 6.6. Working capital of moderately risk averse contractors in experiment set B

6.4.3. Experiment Set C

While considering "Need for Work" is a reasonable strategy for contractors, the extent to which this consideration should be accounted for in the markup percentage has not been studied in the literature. The experiment set presented in this section addresses this gap through having five different groups of contractors in the market who perceive the importance of "Need for Work" consideration differently and thus allocate different boundaries to this criterion in their markup functions. Figure 6.7 shows the experiment results where the growing capitals for the five groups of contractors are presented versus the project ID. It is observed that contractors 1 and 2 who do not take their need for work into consideration in their markup decisions are performing the worst, whereas, contractors 7 and 8 who are adopting a need for work upper margin of 3 % have the best financial performance. Contractors 5 and 6 come in the second rank with using an upper limit of 2%. As for contractors 9 and 10, who are discounting up to 4%, they are increasing their chance of winning the project while decreasing the profit margin radically. On the other hand, contractors 3 and 4 who are discounting up to 1% are not able to immediately secure a contract when they need it. Based on the aforementioned, it can be concluded that considering "Need for Work" strategically and discounting the markup up to 2-3% is the optimal policy for contractors in a competitive market on the long run. All contractors whose working capitals are shown in Figure 6.7 were assigned a moderate risk aversion degree. It should be noted again that this experiment was conducted under different contractors' risk behavior (slightly and extremely risk averse) and the results were consistent regardless of the risk attitude.

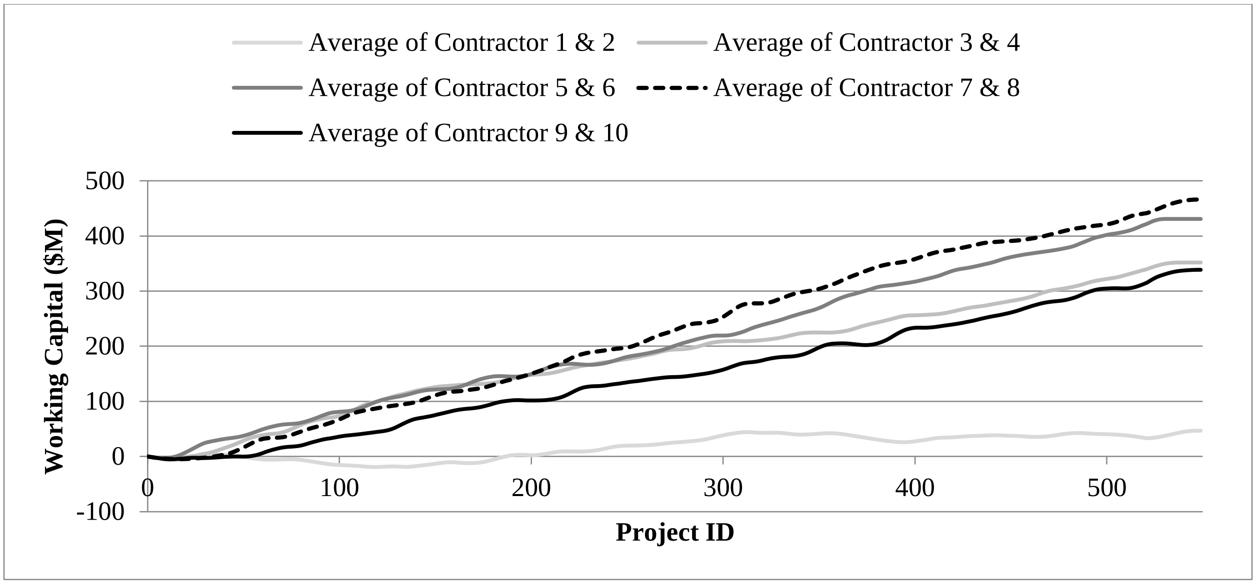


Figure 6.7. Working capital of moderately risk averse contractors in experiment set C

6.5. Chapter Summary

Markup decision can massively impact a contractor's financial performance because the major channel of securing work in the construction industry is still through a variety of competitive bidding mechanisms. The presented study used agent-based modeling as an appropriate framework for analyzing and investigating the impact of risk behavior and need for work on construction contractors' performance in a competitive bidding environment.

Prior to applying agent-based modeling in this study, an extensive literature review was conducted in order to build a rule-based and descriptive markup decision model that replicates behavior of contractors. Then, different experiments were designed and implemented under a variety of scenarios. Obtained results suggest that consideration of risk allowance and need for work has significant impact on contractor's financial success in competitive bidding environments. In particular, it was shown that moderately risk averse contractors consistently outperform other contractors in all market conditions including all levels of project risk. Also, considering 2% to 3%

discount to account for “Need for Work” component in the markup selection led to higher contractors’ chance of financial growth. Therefore, the optimal policy can be concluded to be moderation in both dimensions of risk attitude and need for work. At the limit, not considering need for work and being extremely risk averse appeared to be the least effective strategy a contractor can adopt.

Another main finding of this study is that that the higher the projects’ risk and uncertainty within the market, the more competitive slightly risk averse contractors are compared to moderately risk averse contractors. This emergent behavior is not intuitive. Finally, the results obtained from all sets of experiments converge towards the conclusion that construction market reaches equilibrium where all contractors have gained enough information about their competitors.

CHAPTER 7. VERIFICATION AND VALIDATION OF THE MODELS

“Knowledge is an unending adventure at the edge of uncertainty”. ~ Jacob Bronowski

7.1. Introduction

This chapter explains all the steps taken for verifying and validating the models and results presented in Chapter 3, Chapter 4, Chapter 5, and Chapter 6. Verification is the process of determining whether the programming implementation of the abstract model is correct whereas validation is the process of determining whether the conceptual model is a reasonably true representation of the real world for the purpose of answering the research questions (Sargent, 2013). In other words, verification is concerned with solving the problem right while validation is concerned with solving the right problem (Xiang, Kennedy, Madey, & Cabaniss, 2005).

7.2. Verification

The agent-based simulation platform used in this study, AnyLogic, allows the user to breakdown the model into several computation steps and verify the programming component of each step due to its capability of collecting information on any parameter or process at any time through the simulation. For some specific bidding cycles in several simulation runs, the corresponding calculations of all the process steps were computed manually, compared and verified with the model calculation.

7.3. Validation

The validation task is one of the key challenges in the development of agent-based models where emergent patterns at the aggregate level might not be directly traceable to the individual agents’ micro behavior at the bottom level (Crooks, Castle, & Batty, 2008). There are numerous methods with different level of rigor for verification and validation of simulation models, particularly agent-based models. Depending on the type of the model and available data, a method may be applicable for verification and validation; a model should be verified and validated to the degree needed for the model's intended purpose or application (Sargent, 2013).

One of the most prevalent validation methods is "model-to-model comparison" where the results of the simulation are compared with previous studies on the subject. For this purpose, results of the experiments conducted in the previous chapters were compared with the previous studies in the literature. As mentioned previously, one main result of experiments conducted in Chapter 5 and Chapter 6 were aligned with the literature; moderately risk averse contractors outperform other contractors in competitive markets in a long run.

Another validation method used in this study was parameter variability (sensitivity analysis) where we closely examined how uncertainty in the values of the key input parameters can impact the model output and whether the outcomes are within a reasonable and expected range (Grimm et al., 2010). Considering the capability of the virtual laboratory, different distributions were used for project budget, estimated duration, actual cost, and actual duration in addition to the fact that all experiments are conducted under different scenarios in order to make sure results are consistent. For example, experiment sets B and C in Chapter 6 were conducted with three different contractors' risk attitudes and the result remained consistent.

Robustness analysis or extreme condition test can be performed in order to observe the response of the model to drastic changes such as complete failure in securing a project for a long period of the simulation or unexpected success in early bids.

Structural or conceptual validation ensures that the conceptual model the mathematical/logical/verbal representation (mimic) of the problem entity developed for a particular study (Sargent, 2013). In this study, the bidding process used in the simulation model imitates the actual bidding process happening in reality. For example, one main feature of price-based competitive bidding in the construction industry is that there exists a large input (in the form of requirements, details, drawings and specifications) provided equally for all contractors. Therefore, all contractors bid on the same information as it is in the simulation model.

One important assumption was that contractors have access to other contractors' bidding history. With respect to validation of model assumptions, it is worth mentioning that many contractors have a specific unit in their business development or R&D department that is in charge of collecting market information, tracking and analyzing their competitors. On the other hand, it was assumed that all contractors have the same size, initial working capital, cost estimation accuracy, construction management skills, expertise, and G&A costs in the purpose of removing any possible impact of these factors on the results. With respect to structural validation of the simulation, the bidding process used in the simulation model imitates the actual bidding process happening in reality.

In addition to the above validation techniques, validation of the model through expert judgment is still crucial (Bonabeau, 2002). As part of future work, the simulation models presented in this dissertation can be validated by comparing their results with real case studies or by presenting it to and getting feedback from practitioners and professionals in the field of construction bidding. This is a difficult task especially in the construction business where contractors are most of the time reluctant to reveal their bidding strategies and financial gains or losses.

CHAPTER 8. CONCLUSION

"I can live with doubt and uncertainty and not knowing. I think it is much more interesting to live not knowing than to have answers that might be wrong. If we will only allow that, as we progress, we remain unsure, we will leave opportunities for alternatives. We will not become enthusiastic for the fact, the knowledge, the absolute truth of the day, but remain always uncertain … In order to make progress, one must leave the door to the unknown ajar." ~ Richard Feynman

8.1. Conclusions

This dissertation focused on modeling and analyzing the low-bid lump-sum competitive bidding in the construction industry. The important subject of competitive bidding in construction has attracted research, analysis, and surveys by both the construction academia and industry. A virtual laboratory was developed using agent-based modeling and then it was used in the following chapters:

- to analyze the effectiveness of major quantitative methods in the bidding environment under a variety of scenarios,
- to study the effect of contractors' risk behavior, cost estimating and project management skills, and complexity of projects on contractors' choice of optimal markup, long-term financial growth and market share, and
- to investigate the impact of risk behavior and need for work on contractors' performance.

First, Chapter 3 conducted an extensive review of scientific studies in the field of competitive construction bidding and then categorized the literature into three classes of induction, deduction, and simulation according to their methodological approach. Although previous studies have investigated different aspects of construction bidding from both contractors' and owners' perspectives using analytical and empirical approaches, they failed to understand the dynamics of bidding environment by considering interactions among players. The need for developing a comprehensive model that addresses methodological restrictions and limited applicability of previous research studies was identified. Using a System-of-Systems approach, an agent-based model of the low-bid lump-sum competitive bidding process was developed on a Java-based platform. The model has several advantages over the previous analytical and empirical models including the capability of observing the bidding process dynamics, the interaction between the heterogeneous and learning agents, and the emergent bidding patterns arising from multiple scenarios of market conditions and contractors' attributes. This model can serve as an experimental laboratory that can be used by any potential user (owner or contractor) to evaluate and compare different bidding strategies and project tendering approaches. It can also serve as an educational tool in academic forums and classes to teach construction management students about the bidding process and all its complexities and to allow them to observe interesting dynamics and interactions between the different market constituents from an outsider's perspective.

Second, Chapter 4 introduced a new approach for evaluating the effectiveness of quantitative bidding methods in particular Friedman model and Gates model. While the emphasis of the previous studies was on validity and reliability of those methods using mathematical arguments and retrospective approaches, this study examine their applicability and effectiveness under various scenarios using a prospective approach, agent based modeling. The observations and results from the experiments conducted in this study were not limited to the above question. It also shed some light on the main characteristics of construction bidding environments as observed from micro-behavior of its constituents: contractors and projects. The key conclusions of Chapter 4 are the following:

- Using Friedman model can result in considerably higher number of won projects (higher market share) whereas using Gates model can result in higher profit per project.
- In stable markets comprising rational competitors, the volatility in price of construction services can be due to uncertainty in cost estimating arising from factors such as the complexity of projects and incomplete contract specifications and information.
- One factor contributing to the higher variance in the market is varying set of contractors participating in biddings.
- Although the Fine model has shown a good prospect specifically in competition against unpredictable contractors, the fact that it ignores bid history of specific competitors makes it unfavorable and unreliable in situations where market participants change regularly.
- With the increase in number of rational, sophisticated contractors the benefits unpredictable contractors can get from higher uncertainty in cost estimating will decrease.
- In markets where there is limitation on number of projects a contractor can secure and the bid preparation cost is insignificant (therefore contractors are able to bid on as many projects as they want), the choice of bidding decision model is not a major distinguishing factor.
- Imposing the limitation on bonding capacity can make the market less efficient; it decreases the gap between more effective and less effective contractors and increase average profit per project across the market.
- Requiring a specific number of bid participants will make the market more efficient, lower the average and volatility of market markup, decrease the average profit per project,

increase the gap between market share of more effective and less effective contractors, and reduce the total profit created for contractors in the market.

Third, Chapter 5 formulated the complex interaction among contractors' risk behavior, cost estimating and project management skills, and complexity of projects and then investigated their impact on contractors' choice of optimal markup, long-term financial growth and market share. The results of this study show:

- There is a significant impact of a contractor's risk behavior on its optimal markup and this impact is most significant in markets where projects are of high complexity and uncertainty.
- The inherent risk level of a project is at the core of the markup decision and may result in significant inflation of bid prices in the market.
- Moderately risk averse contractors can financially outperform others in a long run.
- The comparative performance of slightly and extremely risk averse contractors depend on level of cost estimating accuracy and project execution skills of contractors.
- The contractor's good financial performance and market survival depends on his own characteristics, the market conditions and project attributes.
- A better accuracy in the cost estimating of projects and more controlled management of the construction process generate higher profits for most contractors even when their markups decrease.

Fourth, Chapter 6 conducted an extensive literature review in order to build a rule-based and descriptive markup decision model that replicates behavior of contractors. Then, different experiments were designed and implemented under a variety of scenarios. Obtained results suggest that:

- Consideration of risk allowance and need for work has significant impact on contractor's financial success in competitive bidding environments.
- Moderately risk averse contractors consistently outperform other contractors in all market conditions including all levels of project risk.
- Considering up to 2% to 3% discount to account for "Need for Work" component in the markup selection led to higher contractors' chance of financial growth.
- The optimal policy can be concluded to be moderation in both dimensions of risk attitude and need for work.
- At the limit, not considering need for work and being extremely risk averse appeared to be the least effective strategy a contractor can adopt.
- The higher the projects' risk and uncertainty within the market, the more competitive slightly risk averse contractors are compared to moderately risk averse contractors.
- Construction market reaches equilibrium where all contractors have gained enough information about their competitors.

The results presented in this dissertation offer new understandings and insights on the construction bidding environment and recommendations for both owners and contractors' competitive success, which are not available using conventional approaches.

8.2. Future works

Although the current research study was able to fully accomplish its research objectives, a number of additional research directions have been identified. The first four suggested future studies are in continuation of the developed agent-based models in this dissertation. The last two suggested future studies are research problems that I found and formulated when taking a system-of-systems approach to understand construction industry.

8.2.1. Applying Other Markup Models

One of main assumptions of the simulation experiments in this study is that contractors are interested in the long-term expected profit. Although many characteristics of the simulated market is close to the reality of construction markets (for example, markup rates of agent contractors that determined by the quantitative methods are very close to the reported markup rate in the real construction market), the assumption of the long-term expected profit may not apply to all contractors in all situations. Future works can expand on this direction with considering other major quantitative methods including (Carr, 1982, 1987; M. Skitmore & Pemberton, 1994) models. This needs some considerations because Carr and Skitmore-Pemberton models take the true project cost as the reference point and calculate the uncertainties in cost estimation and competitors' bids separately. Components other than mere competition such as opportunity costs (Carr, 1987) can be also taken into consideration.

8.2.2. Adaptive Risk Attitude

In this dissertation, I conclude that moderately risk averse contractors can outperform others in the long run. This is mainly due to their capability in creating a balance between two conflicting paradigms: pursuit of market share and profitability. This study assumes that risk attitude of contractors are fixed regardless of their financial status or market conditions. While the assumption is relevant and valid for investigating the long-term impact of risk attitude on contractors' performance, future studies can relax this assumption. In particular, future works can focus on adaptive risk attitude in two main directions. The first step is to study contractors' organizational culture and risk behavior in order to find out whether and when contractors change their risk attitude. This would help identifying what information and signals contractors look for in the market or their organization in order to act more or less risk averse. Second, new methodologies such as reinforcement learning can be used to help contractors design the optimal dynamic strategy according to their organization, competition, and market conditions. This strategy can be later experimented and compared against other strategies in the virtual laboratory designed and developed in chapter 3.

8.2.3. Dynamic Market

The simulation model developed for the study assumed that the demand for construction works is constant and there is a constant stream of projects. By formulating and developing a market where the demand for construction works is fluctuating, future studies can investigate the following research questions. (1) What would be the optimal risk attitude for a contractor in a market where the demand is fluctuating? (2) Do contractors revise and modify their attitude towards risk? What are their key criteria for this decision? How often do they usually go through this process? (3) Do risk adaptive contractors perform better in constant and fluctuating market conditions?

8.2.4. New Features for Contractors

In all experiments conducted in this study, the number of contractors in the market was kept fixed and there was no newcomer or quitter from the market. Also, the size of a contracting firm was considered constant throughout the simulation while it is not always the case in reality. In future studies, new behaviors for contractors such as entry, exit, expansion, contraction, alliance, and merging can be defined and added to the model if they are aligned with the purpose of the research.

8.2.5. Assessment of the Impact of Public Spending on Macroeconomics of the American Construction Industry

Using advance econometric methods, this study aims to assess the impact of public spending, perceived as a policy tool, on different macroeconomic indicators of the American construction industry including but not limited to construction cost, construction employment, and private investment in construction. To better capture the dynamics of construction economics at macro level, multi-equation time series models such as VAR and VEC will be constructed among more than two variables. Impact assessment of public spending using econometric methods has been received attention from researchers in various disciplines such as economics (Fatás & Mihov, 2001; Ghali, 1998; Mittnik & Neumann, 2001; Mountford & Uhlig, 2009; Pang & Herrera, 2005; Primiceri, 2005), public health (Filmer & Pritchett, 1999), and education (Mandl, Dierx, & Ilzkovitz, 2008; Poterba, 1996). While public spending in construction, mostly on infrastructures, has been perceived as an effective means for policy makers to regulate or enhance the overall economy or specific sectors (Aschauer, 1989; Munnell, 1992), its impact on macroeconomics of the construction industry both in short-term and long-term is not well understood. For example, it is not clear yet how construction public spending encourages or discourages private investments and whether the government plays a role of a competitor for private developers. Using econometric analysis and based on empirical evidences, those scenarios under which construction public spending influences the construction industry both positively and negatively will be determined. Furthermore, by a closer look at the effects of different types and timing of construction public spending, the criteria for the optimal policy will be developed.

8.2.6. Understanding Complex Interdependencies between the Construction Industry and Commodity Markets

Construction materials constitute a considerable portion of a construction project value and have impact on the overall performance of the construction industry. Although there is a rich literature on the importance of construction materials management and its impact on construction projects and project stakeholders (Gallagher & Riggs, 2006; Thomas, Sanvido, & Sanders, 1989; Wambeke, Hsiang, & Liu, 2011), their interdependencies with their production cost components and macroeconomics of the construction industry have been disregarded. It is believed that there is dynamic linkages between the construction industry and associated manufacturing industries and commodity markets. When most construction materials like concrete and structural steel have significant commodity and energy components, understanding the above mentioned interdependencies becomes more vital considering the possibility of global impacts through commodity markets. Robust econometric methods can be utilized to discern the different types of interdependencies (linearity or non-linearity, one-way or two-way linkage, and correlation or causality) between construction materials and markets of their commodity and energy components. Along with investigating these bilateral relations, one step further can be taken with analyzing how macroeconomics of construction industry impacts and/or get impacted by commodity markets such as steel and energy.

LIST OF REFERENCES

Ackoff, R. L. (1971). Towards a system of systems concepts. *Management science, 17*(11), 661-671.

AGC, D. T. a. (2000). Insights in Construction.

Agusdinata, D. B., & DeLaurentis, D. (2008). Specification of system-of-systems for policymaking in the energy sector. *Integrated Assessment, 8*(2).

Agusdinata, D. B., Fry, D. N., & Delaurentis, D. A. (2011). Policies to deal with multimodal transport emissions: a system-of-systems approach. *Transportation Planning and Technology, 34*(2), 109-123.

Ahmad, I. (1990). Decision-support system for modeling bid/no-bid decision problem. *Journal of Construction Engineering and Management, 116*(4), 595-608.

Ahmad, I., & Minkarah, I. (1988). Questionnaire survey on bidding in construction. *Journal of Management in Engineering, 4*(3), 229-243.

Ahmad, I., & Minkarah, I. A. (1987). Optimum mark-up for bidding: a preference-uncertainty trade off approach. *Civil Engineering Systems, 4*(4), 170-174.

Aibinu, A. A., & Pasco, T. (2008). The accuracy of pre - tender building cost estimates in Australia. *Construction Management and Economics, 26*(12), 1257-1269.

Akintoye, A. (2000). Analysis of factors influencing project cost estimating practice. *Construction Management & Economics, 18*(1), 77-89.

Akintoye, A., & Fitzgerald, E. (2000). A survey of current cost estimating practices in the UK. *Construction Management & Economics, 18*(2), 161-172.

Akintoye, A. S., & MacLeod, M. J. (1997). Risk analysis and management in construction. *International journal of project management, 15*(1), 31-38.

Al-Bahar, J. F., & Crandall, K. C. (1990). Systematic risk management approach for construction projects. *Journal of Construction Engineering and Management, 116*(3), 533-546.

Albin, P., & Foley, D. K. (1992). Decentralized, dispersed exchange without an auctioneer: A simulation study. *Journal of Economic Behavior & Organization, 18*(1), 27-51.

An, S.-H., Kim, G.-H., & Kang, K.-I. (2007). A case-based reasoning cost estimating model using experience by analytic hierarchy process. *Building and Environment, 42*(7), 2573-2579.

Art Chaovalitwongse, W., Wang, W., Williams, T. P., & Chaovalitwongse, P. (2011). Data mining framework to optimize the bid selection policy for competitively bid highway construction projects. *Journal of Construction Engineering and Management, 138*(2), 277-286.

Aschauer, D. A. (1989). Is public expenditure productive? *Journal of monetary economics, 23*(2), 177-200.

Asgari, S., Afshar, A., & Madani, K. (2013). Cooperative Game Theoretic Framework for Joint Resource Management in Construction. *Journal of Construction Engineering and Management*.

Attalla, M., & Hegazy, T. (2003). Predicting cost deviation in reconstruction projects: Artificial neural networks versus regression. *Journal of Construction Engineering and Management, 129*(4), 405-411.

Axelrod, R. (1997). Advancing the art of simulation in the social sciences *Simulating social phenomena* (pp. 21-40): Springer.

Axelrod, R. M. (1997). *The complexity of cooperation: Agent-based models of competition and collaboration*: Princeton University Press.

Azar, E., & Menassa, C. C. (2011). Agent-based modeling of occupants and their impact on energy use in commercial buildings. *Journal of Computing in Civil Engineering*.

Azar, E., & Menassa, C. C. (2013). Framework to Evaluate Energy-Saving Potential from Occupancy Interventions in Typical Commercial Buildings in the United States. *Journal of Computing in Civil Engineering, 28*(1), 63-78.

Baccarini, D. (1996). The concept of project complexity—a review. *International Journal of Project Management, 14*(4), 201-204.

Baloi, D., & Price, A. D. (2003). Modelling global risk factors affecting construction cost performance. *International journal of project management, 21*(4), 261-269.

Bankes, S. C. (2002). Tools and techniques for developing policies for complex and uncertain systems. *Proceedings of the National Academy of Sciences, 99*(suppl 3), 7263-7266.

Bashford, H. H. (1996). Small business in the construction industry. *Practice Periodical on Structural Design and Construction, 1*(3), 71-73.

Bazerman, M., & Moore, D. A. (2012). Judgment in managerial decision making.

Bernhardt, K. S., & McNeil, S. (2008). Agent-based modeling: approach for improving infrastructure management. *Journal of Infrastructure Systems*.

Berry, B. J. (1964). Cities as systems within systems of cities. *Papers in Regional Science, 13*(1), 147-163.

Bertelsen, S. (2003a). Complexity–Construction in a new Perspective. *IGLC-11, Blacksburg, Virginia*.

Bertelsen, S. (2003b). *Construction as a complex system.* Paper presented at the proceedings of IGLC.

Bing, L., Tiong, R. L.-K., Fan, W. W., & Chew, D. A.-S. (1999). Risk management in international construction joint ventures. *Journal of Construction Engineering and Management*, *125*(4), 277-284.

Boardman, J., & Sauser, B. (2006). *System of Systems-the meaning of of.* Paper presented at the System of Systems Engineering, 2006 IEEE/SMC International Conference on.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, *99*(suppl 3), 7280-7287.

Boughton, P. D. (1987). The competitive bidding process: beyond probability models. *Industrial Marketing Management*, *16*(2), 87-94.

Bower, J., & Bunn, D. (2001). Experimental analysis of the efficiency of uniform-price versus discriminatory auctions in the England and Wales electricity market. *Journal of Economic Dynamics and Control*, *25*(3), 561-592.

Brockmann, C. (2010). 3 Collusion and corruption in the construction sector. *Modern Construction Economics: Theory and Application*, 29.

Buchanan, M. (2009). Economics: meltdown modelling. *Nature, 460*(7256), 680-682.

Bunn, D. W., & Oliveira, F. S. (2001). Agent-based simulation-an application to the new electricity trading arrangements of England and Wales. *Evolutionary Computation, IEEE Transactions on*, *5*(5), 493-503.

Cagno, E., Caron, F., & Perego, A. (2001). Multi-criteria assessment of the probability of winning in the competitive bidding process. *International Journal of Project Management*, *19*(6), 313-324.

Carlock, P. G., & Fenton, R. E. (2001). System of systems (SoS) enterprise systems engineering for information - intensive organizations. *Systems Engineering, 4*(4), 242-261.

Carr, R. I. (1982). General bidding model. *Journal of the Construction Division, 108*(4), 639-650.

Carr, R. I. (1983). Impact of number of bidders on competition. *Journal of Construction Engineering and Management, 109*(1), 61-73.

Carr, R. I. (1987). Competitive bidding and opportunity costs. *Journal of Construction Engineering and Management, 113*(1), 151-165.

Carr, R. I., & Sandahl, J. W. (1978). Bidding strategy using multiple regression. *Journal of the Construction Division, 104*(1), 15-26.

Chandrashekar, N., Gautam, S., Srinivas, K., & Vijayananda, J. (2007). *Realizing a generic medical image repository for system of systems.* Paper presented at the Commercial-off-the-Shelf (COTS)-Based Software Systems, 2007. ICCBSS'07. Sixth International IEEE Conference on.

Chao, L. C. (2007). Fuzzy logic model for determining minimum bid markup. *Computer‐Aided Civil and Infrastructure Engineering, 22*(6), 449-460.

Chen, J., Jain, R. K., & Taylor, J. E. (2013). Block Configuration Modeling: A novel simulation model to emulate building occupant peer networks and their impact on building energy consumption. *Applied Energy, 105*, 358-368.

Chen, S.-H., & Yeh, C.-H. (2001). Evolving traders and the business school with genetic programming: A new architecture of the agent-based artificial stock market. *Journal of Economic Dynamics and Control, 25*(3), 363-393.

Chua, D., & Li, D. (2000). Key factors in bid reasoning model. *Journal of Construction Engineering and Management*, *126*(5), 349-357.

Chua, D., Li, D., & Chan, W. (2001). Case-based reasoning approach in bid decision making. *Journal of Construction Engineering and Management*, *127*(1), 35-45.

Cincotti, S., Raberto, M., & Teglio, A. (2010). Credit money and macroeconomic instability in the agent-based model and simulator Eurace. *Economics: The Open-Access, Open-Assessment E-Journal, 4*.

Cincotti, S., Raberto, M., & Teglio, A. (2012). *The Eurace macroeconomic model and simulator*. Paper presented at the Agent-based Dynamics, Norms, and Corporate Governance. The proceedings of the 16-th World Congress of the International Economic Association, Palgrave.

Cooke, A. J. (1996). *Economics and construction*: Macmillan London.

Crooks, A., Castle, C., & Batty, M. (2008). Key challenges in agent-based modelling for geo-spatial simulation. *Computers, Environment and Urban Systems, 32*(6), 417-430.

Crowley, L. G. (2000). Friedman and Gates-Another Look. *Journal of Construction Engineering and Management, 126*(4), 306-312.

Cyert, R. M., & March, J. G. (1963). A behavioral theory of the firm. *Englewood Cliffs, NJ, 2*.

Dawid, H., Gemkow, S., Harting, P., Van der Hoog, S., & Neugart, M. (2012). The eurace@ unibi model: An agent-based macroeconomic model for economic policy analysis.

de Neufville, R., & King, D. (1991). Risk and need-for-work premiums in contractor bidding. *Journal of Construction Engineering and Management, 117*(4), 659-673.

De Valence, G. (2010). *Modern Construction Economics: Theory and Application*: Routledge.

Deissenberg, C., Van Der Hoog, S., & Dawid, H. (2008). EURACE: A massively parallel agent-based model of the European economy. *Applied Mathematics and Computation, 204*(2), 541-552.

DeLaurentis, D. (2005a). *A taxonomy-based perspective for systems of systems design methods.* Paper presented at the Systems, Man and Cybernetics, 2005 IEEE International Conference on.

DeLaurentis, D. (2005b). *Understanding transportation as a system-of-systems design problem.* Paper presented at the 43rd AIAA Aerospace Sciences Meeting and Exhibit.

DeLaurentis, D., & Callaway, R. K. (2004). A system ‐ of ‐ systems perspective for public policy decisions. *Review of Policy Research, 21*(6), 829-837.

DeLaurentis, D. A., Crossley, W. A., & Mane, M. (2011). Taxonomy to guide systems-of-systems decision-making in air transportation problems. *Journal of Aircraft, 48*(3), 760-770.

DeLaurentis, P.-C., & DeLaurentis, D. (2010). *Consideration of system of systems and service systems as complimentary approaches for healthcare problems.* Paper presented at the System of Systems Engineering (SoSE), 2010 5th International Conference on.

Dosi, G., & Orsenigo, L. (1994). Macrodynamics and microfoundations: an evolutionary perspective. *Economics of Technology//Amsterdam: North-Holland*, 91-123.

Dozzi, S. P., AbouRizk, S., & Schroeder, S. (1996). Utility-theory model for bid markup decisions. *Journal of Construction Engineering and Management*, *122*(2), 119-124.

Drew, D., & Skitmore, M. (1997). The effect of contract type and size on competitiveness in bidding. *Construction Management & Economics, 15*(5), 469-489.

Drew, D. S. (2010). 4 Competing in construction auctions. *Modern Construction Economics: Theory and Application*, 63.

Drew, D. S., & Skitmore, M. (2006). Testing Vickery's revenue equivalence theory in construction auctions. *Journal of Construction Engineering and Management, 132*(4), 425-428.

Dubois, A., & Gadde, L.-E. (2002). The construction industry as a loosely coupled system: implications for productivity and innovation. *Construction Management & Economics, 20*(7), 621-631.

Dulaimi, M. F., & Shan, H. G. (2002). The factors influencing bid mark-up decisions of large-and medium-size contractors in Singapore. *Construction Management & Economics, 20*(7), 601-610.

Egemen, M., & Mohamed, A. N. (2007). A framework for contractors to reach strategically correct bid/no bid and mark-up size decisions. *Building and Environment, 42*(3), 1373-1385.

El-Adaway, I. H., & Kandil, A. A. (2009). Multiagent system for construction dispute resolution (MAS-COR). *Journal of Construction Engineering and Management*.

El-Mashaleh, M. S. (2012). Empirical framework for making the bid/no-bid decision. *Journal of Management in Engineering, 29*(3), 200-205.

Farmer, J. D., & Foley, D. (2009). The economy needs agent-based modelling. *Nature, 460*(7256), 685-686.

Farmer, J. D., Gallegati, M., Hommes, C., Kirman, A., Ormerod, P., Cincotti, S., . . . Helbing, D. (2012). A complex systems approach to constructing better models for managing financial markets and the economy. *The European Physical Journal Special Topics, 214*(1), 295-324.

Fatás, A., & Mihov, I. (2001). *The effects of fiscal policy on consumption and employment: theory and evidence* (Vol. 2760): Centre for Economic Policy Research.

Fayek, A. (1998). Competitive bidding strategy model and software system for bid preparation. *Journal of Construction Engineering and Management, 124*(1), 1-10.

Fekete, K., Nikolovski, S., Puzak, D., Slipac, G., & Keko, H. (2008). *Agent-based modelling application possibilities for Croatian electricity market simulation.* Paper presented at the Electricity Market, 2008. EEM 2008. 5th International Conference on European.

Filatova, T., Parker, D., & Van der Veen, A. (2009). Agent-based urban land markets: agent's pricing behavior, land prices and urban land use change. *Journal of Artificial Societies and Social Simulation, 12*(1), 3.

Filmer, D., & Pritchett, L. (1999). The impact of public spending on health: does money matter? *Social science & medicine, 49*(10), 1309-1323.

Fine, B. Various unpublished papers based on work of the Costain OR Group.

Flyvbjerg, B., Skamris Holm, M. K., & Buhl, S. L. (2003). How common and how large are cost overruns in transport infrastructure projects? *Transport reviews, 23*(1), 71-88.

Friedman, L. (1956). A competitive-bidding strategy. *Operations research, 4*(1), 104-112.

Fuerst, M. (1976). Bidding models: truths and comments. *Journal of the Construction Division, 102*(1), 169-177.

Gallagher, J., & Riggs, F. (2006). Material price escalation: Allocating the risks. *Construction Briefings*(2006-12).

Gates, M. (1967). Bidding strategies and probabilities. *Journal of the Construction Engrg. Division, 93*(1), 75-110.

Geanakoplos, J., Axtell, R., Farmer, D. J., Howitt, P., Conlee, B., Goldstein, J., . . . Yang, C.-Y. (2012). Getting at systemic risk via an agent-based model of the housing market. *The American Economic Review, 102*(3), 53-58.

Ghali, K. H. (1998). Public investment and private capital formation in a vector error-correction model of growth. *Applied Economics, 30*(6), 837-844.

Gidado, K. (1996). Project complexity: The focal point of construction production planning. *Construction Management & Economics*, *14*(3), 213-225.

Gilbert, G. N. (2008). *Agent-based models*: Sage.

Gordon, C. M. (1994). Choosing appropriate construction contracting method. *Journal of Construction Engineering and Management*.

Grigoroudis, E., & Phillis, Y. (2013). Modeling healthcare system-of-systems: a mathematical programming approach. *Systems Journal, IEEE, 7*(4), 571-580.

Grimm, V., Berger, U., DeAngelis, D. L., Polhill, J. G., Giske, J., & Railsback, S. F. (2010). The ODD protocol: a review and first update. *Ecological modelling*, *221*(23), 2760-2768.

Gruneberg, S. L. (1997). *Construction economics: an introduction*: Macmillan London.

Han, E., & DeLaurentis, D. (2006). *A network theory-based approach for modeling a system-of-systems.* Paper presented at the 11th AIAA/ISSMO Multidisciplinary Analysis and optimization conference.

Han, M., Fan, Y., & Guo, W. (2005). *A modified neural network based on subtractive clustering for bidding system.* Paper presented at the Neural Networks and Brain, 2005. ICNN&B'05. International Conference on.

Han, S. H., & Diekmann, J. E. (2001). Making a risk-based bid decision for overseas construction projects. *Construction Management & Economics, 19*(8), 765-776.

Harris, F., & McCaffer, R. (2013). *Modern construction management*: John Wiley & Sons.

Haskins, C., & Forsberg, K. (2011). International Council on Systems Engineering. *Systems Engineering Handbook: A Guide for System Life Cycle Processes and Activities*.

Hastak, M., & Shaked, A. (2000). ICRAM-1: Model for international construction risk assessment. *Journal of Management in Engineering*, *16*(1), 59-69.

Hatush, Z., & Skitmore, M. (1997). Criteria for contractor selection. *Construction Management & Economics, 15*(1), 19-38.

Hegazy, T., & Moselhi, O. (1994). Analogy-based solution to markup estimation problem. *Journal of Computing in Civil Engineering, 8*(1), 72-87.

Hegazy, T., & Moselhi, O. (1995). Elements of cost estimation: a survey in Canada and the United States. *Cost Engineering-Morgantown, 37*(5), 27-34.

Hillebrandt, P. M. (2000). *Economic theory and the construction industry*: Macmillan London.

Ho, S. P., & Hsu, Y. (2013). Bid compensation theory and strategies for projects with heterogeneous bidders: A game theoretic analysis. *Journal of Management in Engineering, 30*(5), 04014022.

Holt, G. D. (1998). Which contractor selection methodology? *International Journal of project management, 16*(3), 153-164.

Howitt, P., & Clower, R. (2000). The emergence of economic organization. *Journal of Economic Behavior & Organization, 41*(1), 55-84.

Ibbs, C. W., & Crandall, K. C. (1982). Construction Risk: Multivariate Approach. *Journal of the Construction Division, 108*(2), 187-200.

Ioannou, P. G. (1988). Bidding models-symmetry and state of information. *Journal of Construction Engineering and Management*, *114*(2), 214-232.

Izumi, K., & Ueda, K. (1998). *Emergent phenomena in a foreign exchange market: analysis based on an artificial market approach.* Paper presented at the Artificial Life VI.

Izumi, K., & Ueda, K. (2001). Phase transition in a foreign exchange market-analysis based on an artificial market approach. *Evolutionary Computation, IEEE Transactions on, 5*(5), 456-470.

Jamshidi, M. (2008). System of systems engineering-New challenges for the 21st century. *Aerospace and Electronic Systems Magazine, IEEE, 23*(5), 4-19.

Kangari, R. (1995). Risk management perceptions and trends of US construction. *Journal of Construction Engineering and Management, 121*(4), 422-429.

Kartam, N. A., & Kartam, S. A. (2001). Risk and its management in the Kuwaiti construction industry: a contractors' perspective. *International journal of project management, 19*(6), 325-335.

Kilicay-Ergin, N., & Dagli, C. (2008). *Executable modeling for system of systems architecting: An artificial life framework.* Paper presented at the Systems Conference, 2008 2nd Annual IEEE.

Kim, H.-J., & Reinschmidt, K. F. (2010). Effects of contractors' risk attitude on competition in construction. *Journal of Construction Engineering and Management, 137*(4), 275-283.

Kim, H.-J., & Reinschmidt, K. F. (2011). Market structure and organizational performance of construction organizations. *Journal of Management in Engineering*.

King, M., & Mercer, A. (1985). Problems in determining bidding strategies. *Journal of the Operational Research Society*, 915-923.

King, M., & Mercer, A. (1987). Note on a conflict of assumptions in bidding models. *European journal of operational research, 32*(3), 462-466.

King, M., & Mercer, A. (1990). The optimum markup when bidding with uncertain costs. *European journal of operational research, 47*(3), 348-363.

Kirman, A. P. (1997). *The economy as an interactive system.* Paper presented at the SANTA FE INSTITUTE STUDIES IN THE SCIENCES OF COMPLEXITY-PROCEEDINGS VOLUME-.

Knežević, G., Fekete, K., & Nikolovski, S. (2010). *Applying agent-based modeling to electricity market simulation.* Paper presented at the MIPRO, 2010 Proceedings of the 33rd International Convention.

Kotov, V. (1997). Systems of systems as communicating structures. *Object-oriented technology and computing systems re-engineering*, 141-154.

Koushki, P., Al‐Rashid, K., & Kartam, N. (2005). Delays and cost increases in the construction of private residential projects in Kuwait. *Construction Management and Economics, 23*(3), 285-294.

Krishna, V. (2010). Auction theory 2nd ed: Academic Press.

Lan Oo, B., Lo, H.-P., & Teck-Heng Lim, B. (2012). The effect of bidding success in construction bidding. *Engineering, Construction and Architectural Management, 19*(1), 25-39.

Lane, J. A., & Valerdi, R. (2007). Synthesizing SoS concepts for use in cost modeling. *Systems Engineering, 10*(4), 297-308.

Laryea, S., & Hughes, W. (2010). Risk and price in the bidding process of contractors. *Journal of Construction Engineering and Management*.

LeBaron, B. (2000). Agent-based computational finance: Suggested readings and early research. *Journal of Economic Dynamics and Control, 24*(5), 679-702.

LeBaron, B. (2001). Empirical regularities from interacting long-and short-memory investors in an agent-based stock market. *Evolutionary Computation, IEEE Transactions on, 5*(5), 442-455.

Leitch, J. (2000). Profits up- share prices down. *Contract Journal, 12*, 17-18.

Lewe, J.-H., & DeLaurentis, D. A. (2004). *Entity-centric abstraction and modeling of future transportation architectures.* Paper presented at the Proceedings of the 45th Transportation Research Forum, Evanston, IL, Paper 2C-4.

Lewe, J., DeLaurentis, D. A., & Mavris, D. N. (2004). *Foundation for study of future transportation systems through agent-based simulation.* Paper presented at the 24th International Congress of the Aeronautical Sciences.

Lewis, G., Morris, E., Place, P., Simanta, S., Smith, D., & Wrage, L. (2008). *Engineering systems of systems.* Paper presented at the Systems Conference, 2008 2nd Annual IEEE.

Li, H., & Love, P. E. (1999). Combining rule-based expert systems and artificial neural networks for mark-up estimation. *Construction Management & Economics, 17*(2), 169-176.

Li, H., Shen, L., & Love, P. (1999). ANN-based mark-up estimation system with self-explanatory capacities. *Journal of Construction Engineering and Management, 125*(3), 185-189.

Liu, L., & Zhu, K. (2007). Improving cost estimates of construction projects using phased cost factors. *Journal of Construction Engineering and Management, 133*(1), 91-95.

Liu, M., & Ling, Y. Y. (2003). Using fuzzy neural network approach to estimate contractors' markup. *Building and Environment, 38*(11), 1303-1308.

Liu, M., & Ling, Y. Y. (2005). Modeling a contractor's markup estimation. *Journal of Construction Engineering and Management, 131*(4), 391-399.

Liu, S. (2011). Employing system of systems engineering in China's emergency management. *Systems Journal, IEEE, 5*(2), 298-308.

Liu, X., Yang, J., & Tang, B. (2007). *A new agent-based artificial stock market with short-term dynamics.* Paper presented at the Wireless Communications, Networking and Mobile Computing, 2007. WiCom 2007. International Conference on.

Lowe, D., & Skitmore, M. (1994). Experiential learning in cost estimating. *Construction Management and Economics, 12*(5), 423-431.

Lyons, T., & Skitmore, M. (2004). Project risk management in the Queensland engineering construction industry: a survey. *International journal of project management, 22*(1), 51-61.

Magliocca, N., Safirova, E., McConnell, V., & Walls, M. (2011). An economic agent-based model of coupled housing and land markets (CHALMS). *Computers, Environment and Urban Systems, 35*(3), 183-191.

Mahdavi, A., & Hastak, M. (2014). Quantitative Analysis of bidding strategies: a hybrid agent based–system dynamics approach. *Constr. res. congr*, 1129-1138.

Maier, M. W. (1996). *Architecting principles for systems‐of‐systems.* Paper presented at the INCOSE International Symposium.

Mandl, U., Dierx, A., & Ilzkovitz, F. (2008). The effectiveness and efficiency of public spending: Directorate General Economic and Monetary Affairs (DG ECFIN), European Commission.

Mansouri, M., Gorod, A., Wakeman, T., & Sauser, B. (2010). System of systems approach to maritime transportation governance. *Transportation Research Record: Journal of the Transportation Research Board*(2166), 66-73.

Mansouri, M., Gorod, A., Wakeman, T. H., & Sauser, B. (2009). Maritime transportation system of systems management framework: a system of systems engineering approach. *International Journal of Ocean Systems Management, 1*(2), 200-226.

Manthorpe, W. H. (1996). The emerging joint system of systems: A systems engineering challenge and opportunity for APL. *Johns Hopkins APL Technical Digest, 17*(3), 305.

March, J. G. (1991). Exploration and exploitation in organizational learning. *Organization science, 2*(1), 71-87.

March, J. G., & Simon, H. A. (1958). Organizations.

Marzouk, M., & Moselhi, O. (2003). A decision support tool for construction bidding. *Construction Innovation, 3*(2), 111-124.

Meen, D., & Meen, G. (2003). Social behaviour as a basis for modelling the urban housing market: a review. *Urban Studies, 40*(5-6), 917-935.

Metcalfe, J. S., & Foster, J. (2007). *Evolution and economic complexity*: Edward Elgar Publishing.

Miller, L. C. (1962). *Successful management for contractors*: McGraw-Hill.

Mitchell, M. (1977). The probability of being the lowest bidder. *Applied Statistics*, 191-194.

Mittnik, S., & Neumann, T. (2001). Dynamic effects of public investment: vector autoregressive evidence from six industrialized countries. *Empirical Economics, 26*(2), 429-446.

Mizuta, H., & Steiglitz, K. (2000). *Agent-based simulation of dynamic online auctions.* Paper presented at the Simulation Conference, 2000. Proceedings. Winter.

Morin, T. L., & Clough, R. H. (1969). OPBID: Competitive bidding strategy model. *Journal of the Construction Division*.

Mostafavi, A., Abraham, D., & DeLaurentis, D. (2013). Ex-ante policy analysis in civil infrastructure systems. *Journal of Computing in Civil Engineering*.

Mostafavi, A., Abraham, D. M., & Lee, J. (2012). System-of-systems approach for assessment of financial innovations in infrastructure. *Built Environment Project and Asset Management, 2*(2), 250-265.

Mountford, A., & Uhlig, H. (2009). What are the effects of fiscal policy shocks? *Journal of applied econometrics, 24*(6), 960-992.

Munnell, A. H. (1992). Policy watch: infrastructure investment and economic growth. *The Journal of Economic Perspectives*, 189-198.

Myers, D. (2013). *Construction economics: A new approach*: Routledge.

Neugart, M. (2008). Labor market policy evaluation with ACE. *Journal of Economic Behavior & Organization, 67*(2), 418-430.

Ngai, S. C., Drew, D. S., Lo, H. P., & Skitmore, M. (2002). A theoretical framework for determining the minimum number of bidders in construction bidding competitions. *Construction Management & Economics*, *20*(6), 473-482.

Nicolaisen, J., Petrov, V., & Tesfatsion, L. (2001). Market power and efficiency in a computational electricity market with discriminatory double-auction pricing. *Evolutionary Computation, IEEE Transactions on*, *5*(5), 504-523.

Noam, E. M. (1994). Beyond liberalization: From the network of networks to the system of systems. *Telecommunications Policy, 18*(4), 286-294.

North, M., Conzelmann, G., Koritarov, V., Macal, C., Thimmapuram, P., & Veselka, T. (2002). *E-laboratories: agent-based modeling of electricity markets.* Paper presented at the 2002 American Power Conference.

Ofori, G. (1990). *The construction industry: aspects of its economics and management*: NUS Press.

Ofori, G. (1994). Establishing construction economics as an academic discipline. *Construction Management and Economics, 12*(4), 295-306.

Ogunlana, S., & Thorpe, A. (1991). The nature of estimating accuracy: Developing correct associations. *Building and Environment, 26*(2), 77-86.

Oo, B.-L., Drew, D. S., & Lo, H.-P. (2008a). A comparison of contractors' decision to bid behaviour according to different market environments. *International Journal of project management, 26*(4), 439-447.

Oo, B.-L., Drew, D. S., & Lo, H.-P. (2008b). Heterogeneous approach to modeling contractors' decision-to-bid strategies. *Journal of Construction Engineering and Management, 134*(10), 766-775.

Oo, B.-L., Drew, D. S., & Lo, H.-P. (2010). Modeling the heterogeneity in contractors' mark-up behavior. *Journal of Construction Engineering and Management, 136*(7), 720-729.

Osmundson, J. S., Langford, G. O., & Huynh, T. V. (2009). *Emergent Behavior in an Unregulated Financial System of Systems: Economic Meltdown.* Paper presented at the INCOSE International Symposium.

Page, S. E. (2005). Agent based models. *The New Palgrave Dictionary of Economics. Palgrave MacMillan, New York.*

Palmer, R., Arthur, W. B., Holland, J. H., & LeBaron, B. (1999). An artificial stock market. *Artificial Life and Robotics, 3*(1), 27-31.

Pang, G., & Herrera, S. (2005). Efficiency of public spending in developing countries: an efficiency frontier approach. *World Bank Policy Research Working Paper*(3645).

Park, W. R., & Chapin, W. B. (1992). *Construction bidding: Strategic pricing for profit* (Vol. 74): Wiley-Interscience.

Ping Ho, S. (2005). Bid compensation decision model for projects with costly bid preparation. *Journal of Construction Engineering and Management, 131*(2), 151-159.

Poterba, J. M. (1996). Demographic structure and the political economy of public education: National Bureau of Economic Research.

Primiceri, G. E. (2005). Time varying structural vector autoregressions and monetary policy. *The Review of Economic Studies, 72*(3), 821-852.

Pruyt, E., & Thissen, W. (2007). *Transition of the european electricity system and system of systems concepts.* Paper presented at the System of Systems Engineering, 2007. SoSE'07. IEEE International Conference on.

Raftery, J. (1991). *Principles of building economics: an introduction*: BSP Professional Books.

Rice, H., & Heimbach, A. (2007). Why contractors fail: a causal analysis of large contractor bankruptcies. *FMI Quarterly, 2*, 52-74.

Robbins, L. (2007). *An essay on the nature and significance of economic science*: Ludwig von Mises Institute.

Rosenshine, M. (1972). Bidding Models: Resolution of a Controversey. *Journal of the Construction Engrg. Division, 98*(1), 143-148.

Roumeliotis, G. (2011). Global construction growth to outpace GDP this decade. *Reuters*.

Runeson, G., & Skitmore, M. (1999). Tendering theory revisited. *Construction Management & Economics, 17*(3), 285-296.

Russell, S., & Norvig, P. (1995). Artificial intelligence: a modern approach.

Rusu, A., Taggart, D., Desmond, K., & Lopez, H. (2013). *Intelligent and defensive framework for decision-making systems-of-systems with applications to healthcare.* Paper presented at the Systems Conference (SysCon), 2013 IEEE International.

Sage, A. P., & Cuppan, C. D. (2001). On the systems engineering and management of systems of systems and federations of systems. *Information, Knowledge, Systems Management, 2*(4), 325-345.

Said, H., Kandil, A., Nookala, S. B. S., Cai, H., El-Gafy, M., Senouci, A., & Al-Derham, H. (2013). Modeling of the sustainability goal and objective setting process in the predesign phase of green institutional building projects. *Journal of Architectural Engineering*.

Sargent, R. G. (2013). Verification and validation of simulation models. *Journal of Simulation, 7*(1), 12-24.

Seydel, J., & Olson, D. L. (1990). Bids considering multiple criteria. *Journal of Construction Engineering and Management, 116*(4), 609-623.

Shash, A. A. (1993). Factors considered in tendering decisions by top UK contractors. *Construction management and economics, 11*(2), 111-118.

Shen, L., Drew, D., & Zhang, Z. (1999). Optimal bid model for price-time biparameter construction contracts. *Journal of Construction Engineering and Management, 125*(3), 204-209.

Simon, H. A. (1965). *Administrative behavior* (Vol. 4): Cambridge Univ Press.

Skitmore, M. (1991). The construction contract bidder homogeneity assumption: An empirical test. *Construction management and economics, 9*(5), 403-429.

Skitmore, M., & Pemberton, J. (1994). A multivariate approach to construction contract bidding mark-up strategies. *Journal of the Operational Research Society*, 1263-1272.

Skitmore, M., Runeson, G., & Chang, X. (2006). Construction price formation: full - cost pricing or neoclassical microeconomic theory? *Construction management and economics, 24*(7), 773-783.

Skitmore, R. M., & Ng, S. T. (2003). Forecast models for actual construction time and cost. *Building and Environment, 38*(8), 1075-1083.

Skitmore, R. M., Pettitt, A. N., & McVinish, R. (2007). Gates' bidding model. *Journal of Construction Engineering and Management*, *133*(11), 855-863.

Smith, G. R., & Bohn, C. M. (1999). Small to medium contractor contingency and assumption of risk. *Journal of Construction Engineering and Management, 125*(2), 101-108.

Stark, R. M. (1968). Unbalanced bidding models-theory. *Journal of the Construction Engrg. Division, 94*(2), 197-210.

Tassier, T., & Menczer, F. (2001). Emerging small-world referral networks in evolutionary labor markets. *Evolutionary Computation, IEEE Transactions on, 5*(5), 482-492.

Tay, N. S., & Linn, S. C. (2001). Fuzzy inductive reasoning, expectation formation and the behavior of security prices. *Journal of Economic Dynamics and Control, 25*(3), 321-361.

Teglio, A., Raberto, M., & Cincotti, S. (2010). Endogenous credit dynamics as source of business cycles in the EURACE model *Progress in Artificial Economics* (pp. 203-214): Springer.

Tesfatsion, L. (1997a). HOW ECONOMISTS CAN GET ALIFE1.

Tesfatsion, L. (1997b). *A trade network game with endogenous partner selection*: Springer.

Tesfatsion, L. (1998). *Preferential partner selection in evolutionary labor markets: A study in agent-based computational economics.* Paper presented at the Evolutionary programming VII.

Tesfatsion, L. (2002). Agent-based computational economics: Growing economies from the bottom up. *Artificial life, 8*(1), 55-82.

Tesfatsion, L. (2006). Agent-based computational economics: A constructive approach to economic theory. *Handbook of computational economics, 2,* 831-880.

Thomas, H. R., Sanvido, V. E., & Sanders, S. R. (1989). Impact of material management on productivity-A case study. *Journal of Construction Engineering and Management, 115*(3), 370-384.

Unsal, H. I., & Taylor, J. E. (2010). Modeling interfirm dependency: Game theoretic simulation to examine the holdup problem in project networks. *Journal of Construction Engineering and Management, 137*(4), 284-293.

Unsal, H. I., & Taylor, J. E. (2011). An empirical investigation of opportunistic behaviour in project networks and its impact on market efficiency. *The Engineering Project Organization Journal*, *1*(2), 95-106.

Valluri, A., North, M. J., & Macal, C. M. (2009). Reinforcement learning in supply chains. *International journal of neural systems*, *19*(05), 331-344.

Vickrey, W. (1961). Counterspeculation, auctions, and competitive sealed tenders. *The Journal of finance, 16*(1), 8-37.

Voudouris, V., Stasinopoulos, D., Rigby, R., & Di Maio, C. (2011). The ACEGES laboratory for energy policy: exploring the production of crude oil. *Energy Policy, 39*(9), 5480-5489.

Vriend, N. J. (1995). Self-organization of markets: An example of a computational approach. *Computational Economics, 8*(3), 205-231.

Wade, R. L., & Harris, R. B. (1976). LOMARK: a bidding strategy. *Journal of the Construction Division, 102*(1), 197-211.

Wambeke, B. W., Hsiang, S. M., & Liu, M. (2011). Causes of variation in construction project task starting times and duration. *Journal of Construction Engineering and Management, 137*(9), 663-677.

Wang, W. C., Dzeng, R. J., & Lu, Y. H. (2007). Integration of simulation‐based cost model and multi‐criteria evaluation model for bid price decisions. *Computer‐Aided Civil and Infrastructure Engineering, 22*(3), 223-235.

Weidlich, A., & Veit, D. (2008). A critical survey of agent-based wholesale electricity market models. *Energy Economics, 30*(4), 1728-1759.

Weisbuch, G., Kirman, A., & Herreiner, D. (1997). *Market organisation*: Springer.

Weisbuch, G., Kirman, A., & Herreiner, D. (2000). Market organisation and trading relationships. *The economic journal, 110*(463), 411-436.

Wickramasinghe, N., Chalasani, S., Boppana, R. V., & Madni, A. M. (2007). *Healthcare system of systems.* Paper presented at the System of Systems Engineering, 2007. SoSE'07. IEEE International Conference on.

Wickramasinghe, N., Chalasani, S., & Koritala, S. (2012). *The role of healthcare system of systems and collaborative technologies in providing superior healthcare delivery to native american patients.* Paper presented at the System Science (HICSS), 2012 45th Hawaii International Conference on.

Wilhite, A. (2001). Bilateral trade and 'small-world'networks. *Computational Economics, 18*(1), 49-64.

Willenbrock, J. H. (1973). Utility function determination for bidding models. *Journal of the Construction Division, 99*(1), 133-153.

Windrum, P., Fagiolo, G., & Moneta, A. (2007). Empirical validation of agent-based models: Alternatives and prospects. *Journal of Artificial Societies and Social Simulation, 10*(2), 8.

Wood, H. L., & Gidado, K. (2008). *An overview of complexity theory and its application the construction industry.* Paper presented at the 24th Annual ARCOM Conference. Cardiff, UK, Association of Researchers in Construction Management.

Xiang, X., Kennedy, R., Madey, G., & Cabaniss, S. (2005). *Verification and validation of agent-based scientific simulation models.* Paper presented at the Agent-Directed Simulation Conference.

XJTechnologies. (2011). Anylogic overview.

Ye, K., Li, B., & Shen, L. (2012). Key factors considered in compiling tender prices for China's public works projects. *Journal of Management in Engineering, 29*(3), 206-215.

Ye, K., Shen, L., Xia, B., & Li, B. (2014). Key attributes underpinning different markup decision between public and private projects: A China study. *International Journal of Project Management, 32*(3), 461-472.

Zhi, H. (1995). Risk management for overseas construction projects. *International journal of project management, 13*(4), 231-237.

Zhou, H., Jiang, J., & Zeng, W. (2010). *An agent-based finance market model with the continuous double auction mechanism.* Paper presented at the Intelligent Systems (GCIS), 2010 Second WRI Global Congress on.

Zhou, Z., Wang, J., & Botterud, A. (2011). *Agent-based electricity market simulation with plug-in hybrid electric vehicle penetration.* Paper presented at the Power and Energy Society General Meeting, 2011 IEEE.

Zhou, Z., Zhao, F., & Wang, J. (2011). Agent-based electricity market simulation with demand response from commercial buildings. *Smart Grid, IEEE Transactions on, 2*(4), 580-588.

APPENDICES

Appendix 1 - Algorithm of Friedman markup function in Chapter 4

1- Find competitors of a contractor for a given project

Place the related codes here!

2- Find common projects of the contractor and each of the competitors

3- Calculate the bid-to-cost ratio for all common projects

4- Determining the mean and variance of bid-to-cost ratios of the common projects for each contractor

5- Add those means and variances to the collection of "Means" and "Variances"

6- Find the probability of winning using Friedman model

7- Find the optimal markup; the one that maximizes the expected profit.

Appendix 2 - Java codes of Friedman markup function in Chapter 4

```java
int learning = 5;
double sum=0;
competitors.clear();
means.clear();
variances.clear();

if( inBiddingHistory.size() > learning ){

	for(Contractor c: get_Main().allContractors){

		if( get_Main().projects.get(i).interestedContractors.contains(c) == true
&& c != this )
		competitors.add(c);
	}

	// Determining Mean & Variance of previous bid prices
	for( Contractor c: competitors ){
	commonBiddingHistory.clear();
	sum=0;
	mean=0;
	variance=0;
```

```
            for(int n = 0; n < biddingHistory.size() -1 ; n++){

                    if(     this.estimatedCostHistory.get(n)     !=     infinity     &&
c.bidPriceHistory.get(n) != infinity ){
                    this.commonBiddingHistory.add( n );
                    sum += c.bidPriceHistory.get(n)/this.estimatedCostHistory.get(n);
                    }
            }

            if( this.commonBiddingHistory.size() < 1 )
            mean = 1.1;
            else
            mean = sum/this.commonBiddingHistory.size();

            sum=0;
            for(int n = 0; n < biddingHistory.size() -1 ; n++){

                    if(     this.estimatedCostHistory.get(n)     !=     infinity     &&
c.bidPriceHistory.get(n) != infinity ){
                    sum                                                              +=
sqr( (c.bidPriceHistory.get(n)/this.estimatedCostHistory.get(n)) - mean );
                    }
            }

            if( this.commonBiddingHistory.size() < 1 )
            variance = 0.04;
            else
            variance = sum / (this.commonBiddingHistory.size() - 1);

        this.means.add(mean);
        this.variances.add(variance);
        }

        double factor=1;
        double expectedProfit = 1;
        double optimalProfit = 0;

        // Determining the optimalMarkUp when there is enough historical data
        while ( factor <= 1.3 ){
        double probOfWin = 1;

            for( int m=0; m < competitors.size(); m++ ){
            double x = 0;
            x = (factor - means.get(m)) / ( sqrt(variances.get(m)) ) ;
            probOfWin = ( 1 - get_Main().Q(x) ) * probOfWin ;
            }

            expectedProfit = probOfWin * (factor-1) * estimatedCost;

            if(expectedProfit >= optimalProfit){
            optimalProfit = expectedProfit;
            optimalMarkup = factor;
            }

        factor = factor + 0.0001;
```

```
        }

return optimalMarkup;
}

// Determining the markUp randomly because there is NOT enough historical data about competitors
else
return uniform(1.02,1.05);
```

Appendix 3 - Algorithm of Fine (the lowest-bid) markup function in Chapter 4

1- Find the lowest bid in all previous projects of the contractor

Place the related codes here!

2- Calculate the bid-to-cost ratio for all the previous projects

3- Determining the mean and variance of bid-to-cost ratios of the previous projects

4- Find the probability of winning

5- Find the optimal markup; the one that maximizes the expected profit.

Appendix 4 - Java codes of Fine (the lowest-bid) markup function used in Chapter 4

```
int learning = 5;
double sum=0;
competitors.clear();
means.clear();
variances.clear();

if( inBiddingHistory.size() > learning ){

        // Determining Mean & Variance of previous bid prices
        commonBiddingHistory.clear();
        sum=0;
        mean=0;
        variance=0;

                for(int n = 0; n < biddingHistory.size() -1 ; n++){

                        if( this.estimatedCostHistory.get(n) != infinity ){

                                sum                                                     +=
this.lowestPrice.get(n)/this.estimatedCostHistory.get(n);
                        }
                }
```

```
            if( this.inBiddingHistory.size() < 2 )
            mean = 1.05;
            else
            mean = sum/this.inBiddingHistory.size();

            sum=0;
            for(int n = 0; n < biddingHistory.size() -1 ; n++){

                  if(     this.estimatedCostHistory.get(n)     !=     infinity     &&
this.bidPriceHistory.get(n) != infinity ){
                  sum                                                           +=
sqr( ( this.lowestPrice.get(n)/this.estimatedCostHistory.get(n) ) - mean );
                  }
            }

            if( this.inBiddingHistory.size() < 2 )
            variance = 0.02;
            else
            variance = sum / (this.inBiddingHistory.size() - 1);



      double factor=1;
      double expectedProfit = 1;
      double optimalProfit = 0;

      // Determining the optimalMarkUp when there is enough historical data
      while ( factor <= 1.3 ){
      double probOfWin = 1;

            double x = (factor - mean) / ( sqrt(variance) ) ;
            probOfWin = ( 1 - get_Main().Q(x) ) * probOfWin ;


            expectedProfit = probOfWin * (factor-1) * estimatedCost;

            if(expectedProfit >= optimalProfit){
            optimalProfit = expectedProfit;
            optimalMarkup = factor;
            }

      factor = factor + 0.0001;
      }

return optimalMarkup;
}

// Determining the markUp randomly because there is NOT enough historical data about
competitors
else
return uniform(1.02,1.05);
```

Appendix 5 - Java codes of Friedman-Utility markup function used in Chapter 5

```
int learning = 1;
double sum=0;
competitors.clear();
means.clear();
variances.clear();

if (get_Main().projects.get(i).complexity == 1)
	estimatedCostCV = 0.05;
else if (get_Main().projects.get(i).complexity == 2)
	estimatedCostCV = 0.1;
else
	estimatedCostCV = 0.2;

if( inBiddingHistory.size() > learning ){

	for(Contractor c: get_Main().allContractors){

		if( get_Main().projects.get(i).interestedContractors.contains(c) == true
&& c != this )
		competitors.add(c);
	}

	// Determining Mean & Variance of previous bid prices
	for( Contractor c: competitors ){
	commonBiddingHistory.clear();
	sum=0;
	mean=0;
	variance=0;

		for(int n = 0; n < biddingHistory.size() - 1 ; n++){

			if(     this.estimatedCostHistory.get(n)     !=     infinity     &&
c.bidPriceHistory.get(n) != infinity ){
			this.commonBiddingHistory.add( n );
			sum += c.bidPriceHistory.get(n)/this.estimatedCostHistory.get(n);
			}
		}

		if( this.commonBiddingHistory.size() < 1 )
		mean = 1.1;
		else
		mean = sum/this.commonBiddingHistory.size();

		sum=0;
		for(int n = 0; n < biddingHistory.size() -1 ; n++){

			if(     this.estimatedCostHistory.get(n)     !=     infinity     &&
c.bidPriceHistory.get(n) != infinity ){
			sum                                                          +=
sqr( (c.bidPriceHistory.get(n)/this.estimatedCostHistory.get(n)) - mean );
			}
		}
```

```
            if( this.commonBiddingHistory.size() < 1 )
            variance = 0.04;
            else
            variance = sum / (this.commonBiddingHistory.size() - 1);

      this.means.add(mean);
      this.variances.add(variance);
      }

      double factor=1;
      double expectedUtility = 1;
      double optimalUtility = 0;

      // Determining the optimalMarkUp when there is enough historical data
      while ( factor <= 1.5 ){
      double probOfWin = 1;

            for( int m=0; m < competitors.size(); m++ ){
            double x = 0;
            x = (factor - means.get(m)) / ( sqrt(variances.get(m)) ) ;
            probOfWin = ( 1 - get_Main().Q(x) ) * probOfWin ;
            }

            expectedUtility = probOfWin*(1 -exp( -riskav* ((factor-1)*estimatedCost
- 0.5*riskav* sqr(estimatedCostCV*estimatedCost) ) ) );

            if(expectedUtility >= optimalUtility){
            optimalUtility = expectedUtility;
            optimalMarkup = factor;
            }

      factor = factor + 0.0001;
      }

return optimalMarkup;
}

// Determining the markUp randomly because there is NOT enough historical data about
competitors
else
return uniform(1.02,1.05);
```

Appendix 6 - Java codes of multi-attribute markup function used in Chapter 6

```
int learning = 0;
competitors.clear();
double sum = 0;
double average = 0;

if( inBiddingHistory.size() > learning ){
```

```
// Markup Decision: Three Additive Components

        // 1- Competition Effect:  [5, 9] %

        for(Contractor c: get_Main().allContractors){
                if( get_Main().projects.get(i).interestedContractors.contains(c) == true
&& c != this )
                competitors.add(c);
        }

biddingCompetitivenessRank = 1 ;

        for( Contractor c: competitors ){
                if( biddingCompetitivenessTen > c.biddingCompetitivenessTen ){
                sum += 1 ;
                biddingCompetitivenessRank += 1 ; }
        }

        average = sum / competitors.size() ;


        if (average < 0.2)
        component1 = 0.09;
        else if (average >= 0.2 && average < 0.4)
        component1 = 0.08;
        else if (average >= 0.4 && average < 0.6)
        component1 = 0.07;
        else if (average >= 0.6 && average < 0.8)
        component1 = 0.06;
        else if (average >= 0.8)
        component1 = 0.05;

        // 2- Need for work : [-4, 0] %

        if (consideringNeedForWork == 0){
        component2 = 0;
        }


        else if (consideringNeedForWork == 1){

        financialStatus = workingCapital - initialWorkingCapital;
        needForWork = 1 - currentWorkVolume/workInProgressLimit ;

        if (financialStatus > 0){

        if (needForWork < 0)
        component2 = 0.00;
        else if (needForWork >= 0 && needForWork < 0.3)
        component2 = -0.00125;
        else if (needForWork >= 0.3 && needForWork < 0.6)
        component2 = -0.0025;
        else if (needForWork > 0.6)
        component2 = -0.005;
        }
```

```
else {

if (needForWork < 0)
component2 = 0.00;
else if (needForWork >= 0 && needForWork < 0.3)
component2 = -0.0025;
else if (needForWork >= 0.3 && needForWork < 0.6)
component2 = -0.005;
else if (needForWork > 0.6)
component2 = -0.01;
}
}


else if (consideringNeedForWork == 2){

financialStatus = workingCapital - initialWorkingCapital;
needForWork = 1 - currentWorkVolume/workInProgressLimit ;

if (financialStatus > 0){

if (needForWork < 0)
component2 = 0.00;
else if (needForWork >= 0 && needForWork < 0.3)
component2 = -0.0025;
else if (needForWork >= 0.3 && needForWork < 0.6)
component2 = -0.005;
else if (needForWork > 0.6)
component2 = -0.01;
}

else {

if (needForWork < 0)
component2 = 0.00;
else if (needForWork >= 0 && needForWork < 0.3)
component2 = -0.005;
else if (needForWork >= 0.3 && needForWork < 0.6)
component2 = -0.01;
else if (needForWork > 0.6)
component2 = -0.02;
}
}


else if (consideringNeedForWork == 3){

financialStatus = workingCapital - initialWorkingCapital;
needForWork = 1 - currentWorkVolume/workInProgressLimit ;

if (financialStatus > 0){

if (needForWork < 0)
component2 = 0.00;
```

```
else if (needForWork >= 0 && needForWork < 0.3)
component2 = -0.00375;
else if (needForWork >= 0.3 && needForWork < 0.6)
component2 = -0.0075;
else if (needForWork > 0.6)
component2 = -0.015;
}

else {

if (needForWork < 0)
component2 = 0.00;
else if (needForWork >= 0 && needForWork < 0.3)
component2 = -0.0075;
else if (needForWork >= 0.3 && needForWork < 0.6)
component2 = -0.015;
else if (needForWork > 0.6)
component2 = -0.03;
}
}


else if (consideringNeedForWork == 4){

financialStatus = workingCapital - initialWorkingCapital;
needForWork = 1 - currentWorkVolume/workInProgressLimit ;

if (financialStatus > 0){

if (needForWork < 0)
component2 = 0.00;
else if (needForWork >= 0 && needForWork < 0.3)
component2 = -0.005;
else if (needForWork >= 0.3 && needForWork < 0.6)
component2 = -0.01;
else if (needForWork > 0.6)
component2 = -0.02;
}

else {

if (needForWork < 0)
component2 = 0.00;
else if (needForWork >= 0 && needForWork < 0.3)
component2 = -0.01;
else if (needForWork >= 0.3 && needForWork < 0.6)
component2 = -0.02;
else if (needForWork > 0.6)
component2 = -0.04;
}
}



// 3- Risk Allowance : [0, 7] %
```

```
        // 0 means Slightly risk averse
        // 1 means Moderately Risk Averse
        // 2 means Extremely risk Averse

        if (riskAttitude == 0){
        if (get_Main().projects.get(i).riskLevel == 0)
        component3 = 0.00;
        if (get_Main().projects.get(i).riskLevel == 1)
        component3 = 0.02;
        }

        else if (riskAttitude == 1){
        if (get_Main().projects.get(i).riskLevel == 0)
        component3 = 0.01;
        if (get_Main().projects.get(i).riskLevel == 1)
        component3 = 0.03;
        }

        else if (riskAttitude == 2){
        if (get_Main().projects.get(i).riskLevel == 0)
        component3 = 0.02;
        if (get_Main().projects.get(i).riskLevel == 1)
        component3 = 0.04;
        }

return 1 + component1 + component2 + component3 + uniform(0,0.00100);
}

else
return uniform(1.05,1.1);
```

Appendix 7 - Computation

This appendix briefly explains the way the developed agent-based model performs computations in consecutive steps. Because the sheer amount of computations is very high, only one time unit of the simulation is broken down and interaction of computational components of the model is described. This appendix presents the time unit #10 of the simulation experiment in Chapter 5. In the experiment, there are nine contractors with different risk attitude (in other words, with different risk coefficient for the equation 5.4). The estimating accuracy and project management skills of all contractors are “Normal”. Project complexity is chosen randomly from low to high. The following are the steps the model takes to simulate the 11th bidding situation:

1- The 11^{th} project (Project ID = 10) is generated. The estimated budget of the project is $100M. The estimated duration is 29 weeks. The complexity level of the project is low.

2- The contractors observe the project and its attributes. They enter the bidding process.

3- The contractors estimate the cost of the project using the following function:

```
if (estimatingAccuracy == "Normal")
      {estimatedCost = pert(0.90, 1.10, 1.00)*p.marketBudget;
      }
else if (estimatingAccuracy == "Improved")
      {estimatedCost = pert(0.95, 1.05, 1.00)*p.marketBudget;
      }
```

The table below presents the estimated cost of the project for each contractor:

Contractor	The Estimated Cost for Project #11 (M$)
1	96.073
2	95.003
3	108.957
4	102.822
5	98.522
6	99.558
7	99.223
8	97.252
9	103.848

4- The contractors determine their optimal markup using the equation 5.4 that combines Friedman Model and Utility Theory. First, a contractor, let's say contractor 5, calculates the bid-cost estimate ratio for all common past project of the competitors. Let's do this for one of the competitors of contractor 5, contractor 3. The table below presents the past cost estimates of contractor 5 and the past bid prices of contractor 3. Then it calculates the bid-cost ratio:

Project #	Cost Estimate of Contractor 5	Bid Price of Contractor 3	Bid-Cost Ratio
1	105.507	96.846	0.918
2	93.07	105.037	1.129
3	102.435	111.757	1.091
4	103.417	105.584	1.021
5	97.878	116.626	1.192
6	102.88	106.443	1.035
7	103.116	101.397	0.983

8	104.563	111.323	1.065
9	94.015	104.178	1.108
10	97.507	114.65	1.176

The table below presents the mean and variance of the bid-cost estimate ratio for contractor 5's competitors:

Competitor of Contractor 5	**Mean of Bid-Cost Estimate Ratio**	**Variance of Bid-Cost Estimate Ratio**
Contractor 1	1.118	0.025
Contractor 2	1.08	0.003
Contractor 3	1.072	0.007
Contractor 4	1.103	0.016
Contractor 6	1.142	0.038
Contractor 7	1.143	0.018
Contractor 8	1.2	0.049
Contractor 9	1.178	0.039

Using the above means and variances, contractor 5 generates a normal distribution of the bid-cost estimate ratio that characterizes the behavior of each competitor. The next step is to solve the optimization problem formulated as the equation 5.4 and find the optimal markup. The table below presents the optimal markup and bid price of all contractors:

Contractor	**Optimal Markup**	**Bid Price (M$)**
1	1.032	99.109
2	<u>1.036</u>	<u>98.471</u>
3	1.044	113.773
4	1.038	106.719
5	1.042	102.64
6	1.045	104.008
7	1.041	103.261
8	1.042	101.347
9	1.05	109.082

As the above table shows, the winner of the bidding is contractor 2. The interesting observation is the fact that the lowest markup has not won the bidding. The next step is to determine the actual cost and duration of the project for contractor 2.

5- The actual cost of the project turns out to be $92.228M. Contractor 2 uses the following function to determine the actual cost given the complexity level of the project and its project management skill:

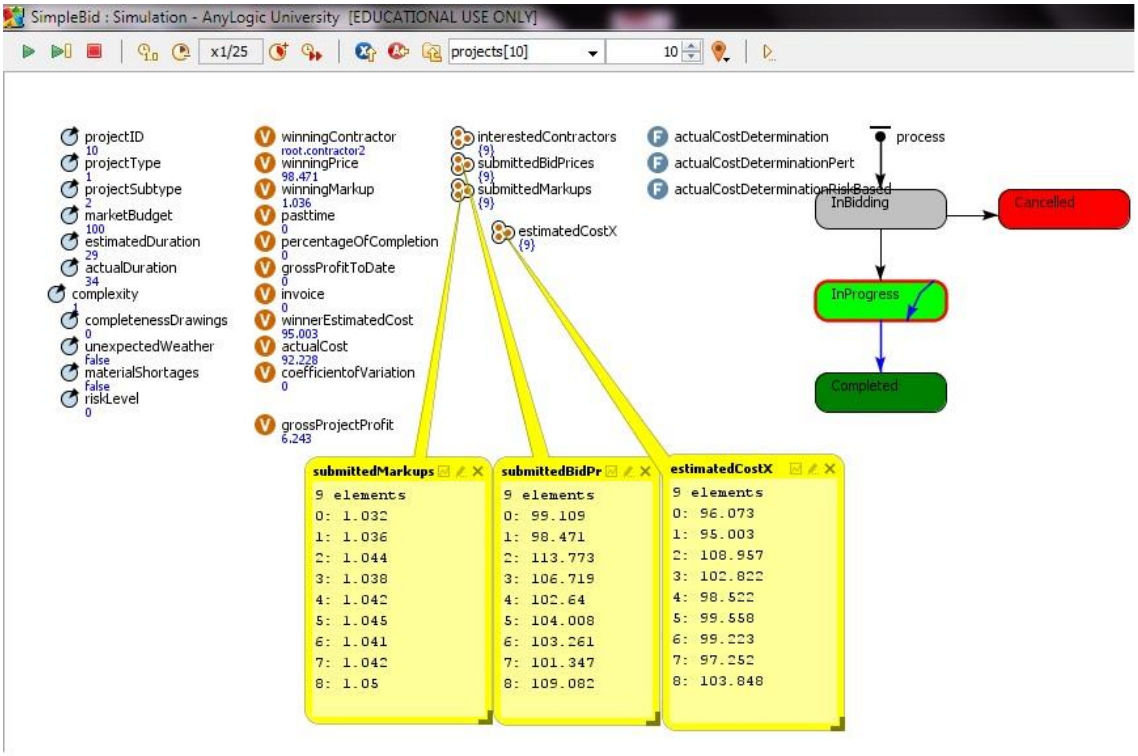
```
if (complexity == 3)
{ if (c.projectExecution == "Normal")
       {actualCost = triangular(1.05,1.15,1.1)*c.estimatedCost*(1-c.GAPercentage);
       }
  else if (c.projectExecution == "Improved")
    {actualCost = triangular(1.025,1.125,1.075)*c.estimatedCost*(1-c.GAPercentage);
    }
 }

else if (complexity == 2)
{ if (c.projectExecution == "Normal")
       {actualCost = triangular(1.0,1.1,1.05)*c.estimatedCost*(1-c.GAPercentage);
       }
  else if (c.projectExecution == "Improved")
    {actualCost = triangular(0.975,1.075,1.025)*c.estimatedCost*(1-c.GAPercentage);
    }
 }

else if (complexity == 1)
{ if (c.projectExecution == "Normal")
       {actualCost = triangular(0.95,1.05,1.0)*c.estimatedCost*(1-c.GAPercentage);
       }
  else if (c.projectExecution == "Improved")
    {actualCost = triangular(0.925,1.025,0.975)*c.estimatedCost*(1-c.GAPercentage);
    }
 }
```

6- The actual duration of the project turns out to be 34 weeks (time units).

The following is a screenshot of the model that presents the attributes and results related to the project 11 (ID = 10).


SimpleBid : Simulation - AnyLogic University [EDUCATIONAL USE ONLY]
x1/25
projects[10]
10
projectID
10
projectType
1
projectSubtype
2
marketBudget
100
estimatedDuration
29
actualDuration
34
complexity
1
completenessDrawings
0
unexpectedWeather
false
materialShortages
false
riskLevel
0
winningContractor
root.contractor2
winningPrice
98.471
winningMarkup
1.036
pasttime
0
percentageOfCompletion
0
grossProfitToDate
0
invoice
0
winnerEstimatedCost
95.003
actualCost
92.228
coefficientofVariation
0
grossProjectProfit
6.243
interestedContractors
{9}
submittedBidPrices
{9}
submittedMarkups
{9}
estimatedCostX
{9}
actualCostDetermination
actualCostDeterminationPert
actualCostDeterminationRiskBased
process
InBidding
Cancelled
InProgress
Completed
submittedMarkups
9 elements
0: 1.032
1: 1.036
2: 1.044
3: 1.038
4: 1.042
5: 1.045
6: 1.041
7: 1.042
8: 1.05
submittedBidPr
9 elements
0: 99.109
1: 98.471
2: 113.773
3: 106.719
4: 102.64
5: 104.008
6: 103.261
7: 101.347
8: 109.082
estimatedCostX
9 elements
0: 96.073
1: 95.003
2: 108.957
3: 102.822
4: 98.522
5: 99.558
6: 99.223
7: 97.252
8: 103.848