Quantitative Analysis of bidding strategies: a hybrid agent based–system dynamics approach

Arash MAHDAVI[1] and Makarand HASTAK[2]

[1] Graduate Research Assistant, Division of Construction Engineering and Management, Purdue University, West Lafayette, IN 47907, PH (765) 496-2046; email: amahdavi@purdue.edu

[2] Professor and Head, Division of Construction Engineering and Management, Purdue University, West Lafayette, IN 47907, PH (765) 494-0641; FAX (765) 494-0644; email: hastak@purdue.edu

ABSTRACT

Economic slowdown and construction demand shrinkage reduces the profit backlog for construction contractors and bites into their profit margin. The resulting fierce competition for jobs forces construction companies to look for more sophisticated analytical tools to analyze and improve their bidding strategies. For each contractor, bidding strategy is a decision-making process that is driven by the firm's financial goals with the final objective of maximizing the firm's gross profit and surpassing the breakeven point. This paper proposes a methodology to model and analyze different bidding strategies with hybrid agent based-system dynamics (AB-SD) simulation. To capture the winning ratio of different bidding strategies, two generic types of agents are defined: "Regular" contractors, for whom the markup calculation process is only an internal decision; and "Learning" contractors, who, as adaptive agents, gradually enhance their prediction capabilities with learning mechanisms. The results of demonstrative simulations based on the proposed methodology show that the learning capability of a construction firm can effectively improve its bid-hit ratio and financial performance.

INTRODUCTION

Construction is a major industry worldwide and its contribution to a country's gross domestic product (GDP) is so extensive that it is usually regarded as an economic indicator for its development. This sector is the largest industrial employer in most countries, accounting for around 7% of the total employment worldwide (Horta 2012). Additionally, the general characteristics and financial aspects of the construction industry are different compared to other industries (Tserng 2011). Some of these characteristics and risks include the construction of unique products and long project durations, which makes them vulnerable to external changes and increases their operational risks. Furthermore, the construction process is quite complicated, consisting of multiple stakeholders who are reliant on the financial stability of each other. Moreover, contractors are, to a great extent, prone to insufficient liquidity. These characteristics contribute in many ways to the high business failure rate in the construction industry (Kangari et al. 1992) and to a relatively high proportion of insolvencies compared with the rest of the economy.

Bidding efficiency has an extensive effect on the financial stability of a construction firm and its strategic objectives since its performance will affect both the

profit backlog of the contractor and the profit margin of each winning project. The most crucial decision in the bidding process, which is the main output of the bidding unit, is the markup decision. The markup consists of both the job and office overheads as well as project contingencies and profit. Important factors in markup decision are the change or adaptation of the strategy and learning process. These factors include the control and adjustment of bidding strategies based on the external environment, business objectives, and experience.

Business organizations have the ability to change their structures and strategies through adaptation and learning. This ability to learn from their internal and external environments gives business organizations, including contractors, a constant state of readiness for change and improvement. Therefore, a bidding model with adaptation and learning capabilities would provide a better understanding of the actual practice of the competitive bidding.

This paper first describes the process of learning and adaptation in the competitive bidding process, and then presents an agent-based model to model the bidding environment considering the effect of sub-contracting in a network that is representative of the business relationships between specific contractors and their sub-contractors.

RESEARCH METHODOLOGY
This research was conducted in five phases:
- Phase-1: The initial phase was a literature review to formulate the needed information for modeling and measuring the financial status (as the main strategic objective) of the contractor and its effect on the bidding strategy.
- Phase-2: The model abstraction phase concluded with mapping the model boundary, identification of the effective parameters and actions inside the contractor's organization, which are necessary for modeling the agents' behavior and interaction.
- Phase-3: In this phase, model implementation, the information obtained in the literature review and mapping phases were utilized to develop the model. This includes specifications for the model's initial conditions, structure, decision rules, learning mechanisms, and tests for consistency with the purpose and boundary.
- Phase-4: The fourth phase of the research methodology included data collection and validation. Robustness under extreme conditions and its sensitivity to the initial conditions inside the model scope were tested.
- Phase-5: Finally, in the scenario analysis phase, one exemplary scenario was specified and analyzed in detail.

MODELING APPROACH
Figure 1 shows a general framework that illustrates the rationale behind simulating bidding competitions with adaptive agents. In this framework, the most fundamental information source for an agent (contractor) during decision-making is its "beliefs," which originate from the contractor's desires and goals. Desires and goals are defined based on the contractor's strategic objectives. As an adaptive agent, the contractor is capable of updating its beliefs or knowledge from two sources: its

current state (financial, functional, or competitive) and feedback from its interactions with other agents (competitors, subcontractors, and owners). In each competition, multiple agents with similar or different beliefs and states compete against each other to win the competition. Assuming that all the agents can estimate the proposed projects costs with the same accuracy, the individual markups would be the differentiator between the competitors.
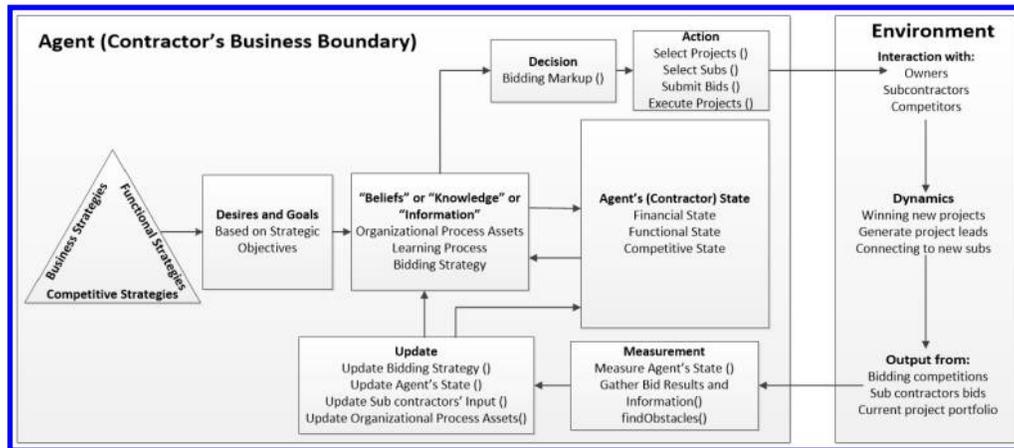

Figure 1. General framework of the rationale behind simulating bidding competitions with adaptive agents

In this study, internal behavior inside the organizational boundary of each contractor (agent) is modeled with a combination of System Dynamics (Forrester, 1976) and Statecharts (Harel, 1987). Two types of agents are defined using these simulation paradigms. These two agent types are almost identical except in their adaptation and learning mechanism. Therefore, the agents are identified as "Regular" (with a simple adaptation mechanism but with no learning capability) and "Learning" (with an adaptation mechanism which utilizes the learning capability to make decisions based on the competitors' behavior). The overall model could be classified as hybrid AB–SD simulation. Swinerd and McNaught (2012) identified three classes of design for hybrid AB–SD simulation. These three classes are integrated, interfaced, and sequential. In this study, we utilized the integrated class, which incorporates the feedback between modules, representing a continuous, fluid process. The ABM–SD integrated hybrid design used in this research uses SD modules which are built within the agents of an ABM module (agents with rich internal structure).

Finally, a network consisting of a combination of these two types of agents was developed to model the construction bidding environment. The interface between contactors (agents) is their markup decision at each time step that distinguishes the winner of each bid.

Data Selection and Data Types

The average financial statements of member companies of the Construction Financial Management Association (CFMA) were used as the initial condition of the financial data input to the contractor's agent. All the initial parameters and financial data for the agents were the same for comparison reasons. The project size and overhead ratio were generated randomly from uniform distributions. The user could

define the number of bidders at the beginning of the simulation; however, a network of three learning and four regular contractors was used for the prototypical model. It was assumed that all contractor agents had no cumulative profit at the beginning of the study, which makes it possible to apply this model to a newly established construction firm and makes the outcomes clearer since it does not mix the simulation results with the previous profits of the contractor. The "regular contractor" picks its markup from a uniform distribution (as an approximation of the range of acceptable markups) and only changes this strategy when it senses a dramatic change in its financial status. In contrast, the "learning contractor" tries to learn the markup distribution of its competitors while taking advantage of its flexibility to change its strategy based on its financial status.

Financial State and Bidding Strategy

Contractors estimate the cost of each project and multiply it by the markup to get their gross profit. Then, offering this markup, they bid in competition against other contractors. Once the project is awarded, contractors can reasonably expect to make a profit from the project. Therefore, the contractor acquires the bid profit, which then becomes a profit pool for future realization. If a contractor wins another project concurrently or during the execution of other projects, all profit estimates from different projects will be accumulated in the backlog of future profit flows. Execution of each previously won project is regarded as the process of realizing the estimated profits from the bid gross profit pool. As a project progresses, the gross profit, which is the estimated profit at the bidding phase, will be realized and accumulated (assuming no loss in gross profit during execution). This generic process of profit flow, which is used in this study, is based on a system dynamic model developed by Cui et al. (2005) and is illustrated in Figure 2.
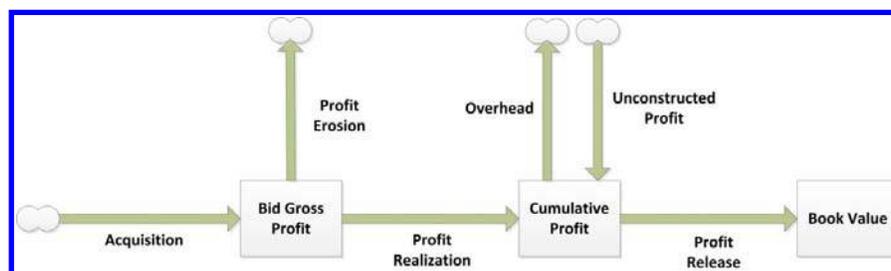

Figure 2. Construction Profit Chain (Cui et al., 2005)

In this study, the markup decision is linked to the financial state of the contractor. To gauge the financial state, a profit chain is built into each agent, and bidding decisions are linked to the level of "Bid Gross Profit" stock, which is representative of the profit backlog resulted from successful prior bids. To capture the financial state at each time step, statecharts are utilized in the model (Figure 3). A statechart is an extended version of state diagrams and is a visual construct that enables the definition of an event and time driven behavior. Our statecharts for both types of agents have the same states, and transitions are triggered based on similar thresholds. Thus, the agents could be in one of three possible states (normal, panic,

and desperate) during a given time step. These three states are linked to a range of bid gross profit levels. Transition between these three states is triggered by reaching a 4 million threshold from normal to panic and 3.5 million from panic to desperate. It is assumed that all contractor agents initially have 5 million dollars in their bid gross profit stock; therefore, the initial state of all agents is normal. In a more detailed model, these thresholds should be linked to the volume of work which is needed to reach the breakeven point. For the purpose of our study these numbers are assumed to be exactly the same for all the agents in order to make the results comparable.

In addition to the financial state, we need to incorporate the bidding strategy of the contractor as a part of its representative agent behavior. The complexity of a bidding decision requires a comprehensive model for bidding decision-making that integrates the learnable, adaptive, and random features of the system. Figure 3 illustrates a complex adaptive bidding unit. The diagram follows the graphic notations in system dynamics and statecharts. This illustration shows the adaptive behavior of a contractor in both cases of regular and learning agents in our model.
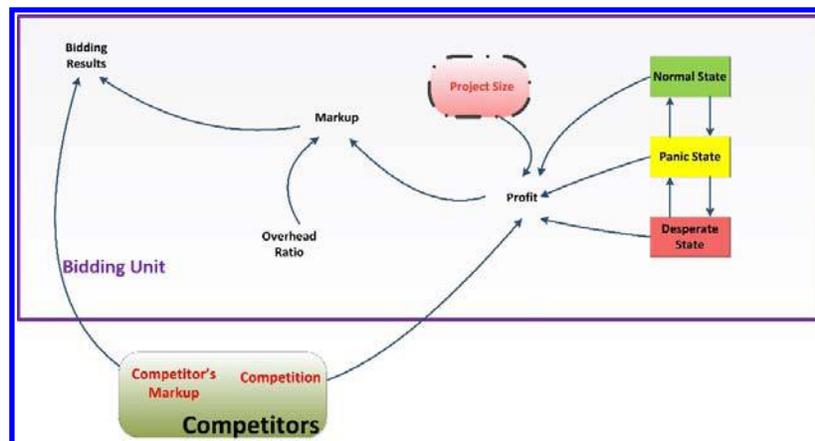

Figure 3. Complex Adaptive Bidding Unit

In the case of regular agents, they do not explicitly gather information about the results of each bidding competition but rather only change their schema when their gross profit margin goes below a certain threshold. They calculate their profit based on the number of competitors in each bid. If the number of competitors is below 15, they consider it to be a low competition and therefore come up with a high profit (in our model 9 %). If the number of competitors is above 15, then they will reduce their profit to 2% to increase their chance of winning under high competition.

Besides adding overhead to this profit, in order to incorporate the financial state in their decision, a parameter called "*ObjectiveWinningChance*" is also multiplied to the previously calculated profit. "*ObjectiveWinningChance*" is a reduction factor that reduces the regular profit levels when the contractor is in financial distress. This parameter is linked to a statechart that keeps track of the current state of the contractor based on its current bid gross profit, which is an indicator of the contractor's expected future profit.

Markup = *Overhead + Profit*ObjectiveWinningChance*

A regular agent is only capable of adapting itself by reducing its profit to increase its chances of winning the next bid. This adaptive behavior is not based on learning or gaming experience from past competitions and increases the winning chance by an unknown quantity.

In the case of the learning contractor agent, they have access to a database of previous winners' markups. Therefore, the expected value and standard deviation of previous markups can be calculated; and based on that information, an objective probability of winning can be calculated for each bidding competition. Learning contractors come up with their optimum markup first based on the historical data accumulated over time. Subsequently, depending on their bid gross profit state, the parameter "*ObjectiveWinningProbability*" will be decided, which is analogous to the "*ObjectiveWinningChance*" for regular contractors. Finally, because all learning agents have access to the same database, their *OptimumMarkup* at each time step is the same. To resolve this uniformity issue, a small random number is added to each optimum markup to add variety to learning agents' markups.

*OptimumMarkup = ExpectedMarkup - sqrt(Variance)*ObjectiveWinningProbability*
Markup = OptimumMarkup + uniform (0.001, 0.002)

The difference between these two practices is that learning contractors can learn from the prior markups of their competitors and also know the probability of winning based on their strategy. As described in Table 1, the "*ObjectiveWinningChance*" and "*ObjectiveWinningProbability*" variables are linked to these states. For example, a regular agent, in the desperate state, decreases its profit by 10% in order to increase the chance of winning the bid. On the other hand, a learning agent, in the desperate state, decreases the expected markup by one standard deviation, which increases its chance of winning to 84%.

Table 1. States of each type of agent and its effect on the markup decision

	Triggered by condition:	
	Transition from Normal to Panic = BidGrossProfit <4	
	Transition from Panic to Normal = BidGrossProfit >=4	
	Transition from Panic to Desperate = BidGrossProfit <3.5	
	Transition from Desperate to Panic = BidGrossProfit >=3.5	
	Effect on the Regular Agent (multiplied to the Profit)	**Effect on the Learning Agent** (multiplied to the SD of Winners' Markup)
	Normal State = ObjectiveWinningChance = 1 *Panic State* = ObjectiveWinningChance = 0.95 *Desperate State* =ObjectiveWinningChance = 0.9	*Normal State* = ObjectiveWinningProbability = 0.5 *Panic State* = ObjectiveWinningProbability = 0.75 *Desperate State* =ObjectiveWinningProbability = 1.0

(Diagram at left: Normal State → Panic State → Desperate State with bidirectional transition arrows)

During the model execution, one bidding competition is taking place at each time step. All the agents (contractors) participate in the competition and offer their bid price. A function inside the model then gathers all the proposed markups of all the participant agents in the bidding competition and grants the project to the winner who has the minimum markup of all participants.

NETWORK OF CONTRACTORS IN A BIDDING ENVIRONMENT

The secondary objective of this study was to examine the effect of sub-contracting and the profit distribution network on the financial performance of the firm. In reality, general contractors (the winner of each bidding competition) usually are not capable of finishing projects alone. General contractors must subcontract some portion of the project to other contractors (who become their sub-contractors). In other words, the winning contractor shares a portion of profit by subcontracting work to the other connected contractors. In practice, some specialized contractors only work as sub-contractors and therefore never bid for a project alone. Special trade contractors are not modeled in this research since incorporating them would require detailed information about each project's specifications.

As a very preliminary and simplified attempt to capture this mechanism and as a proof of concept, we assumed that at each time step, the winner of the competition only acquires 50% of the gross profit. The remaining 50% profit will be equally divided between the other contractors that are contracted by the winner. These connected agents are presumed to transform into the sub-contractors of the winning contractor based on the assumption that the general contractor is only capable of building 50% of the job in-house and must sub-contract the remaining work to the other contractors with whom previously established business relationships exist. Therefore, in each bidding competition, a contractor could be the winner and receive 50% of the gross profit; or if he is connected to the winning contractor instead, the contractor transforms to a sub-contractor and receives a share of the profit. If a contractor is neither the winner nor connected to the winner, it gets no share of the profit. The network used for the analysis of the bidding environment in this paper is a small world network, consisting of three learning agents and four regular agents with five connections per agent and a neighbor link fraction of 0.8 (80%). The model is capable of generating different compositions based on the user definition; two examples of alternative networks are shown in Figure 4. It should be mentioned that the effect of these network on the overall efficiency of the bidding strategy needs a very comprehensive study, while here we only tried to show a simplified case of how this mechanism could be captured in an AB simulation by incorporating the network topology of the links between the agents.
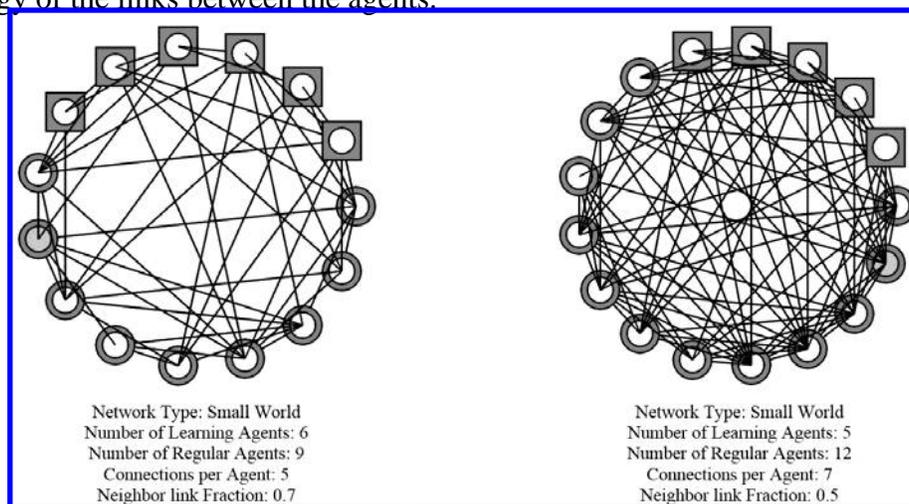

Network Type: Small World
Number of Learning Agents: 6
Number of Regular Agents: 9
Connections per Agent: 5
Neighbor link Fraction: 0.7

Network Type: Small World
Number of Learning Agents: 5
Number of Regular Agents: 12
Connections per Agent: 7
Neighbor link Fraction: 0.5

Figure 4. Two possible compositions of the contractors' network

SIMULATION RESULTS AND VALIDATION

Two types of agents (learning and regular) are used to model a demonstrative example of a network of contractors and sub-contractors. Simulation was run for 120 time steps, equivalent to 10 years of real time. Since only one bidding occurs at each time step, a total of 120 competitions is modeled during the simulation time. A visual representation was designed for the results of the simulation (Figure 5). In this representation, learning agents are identified with squares and regular agents with circles. The winner of each bidding competition is highlighted by a blue (dark) inner circle. Additionally, the agents show a change in their color with a change in their current state.
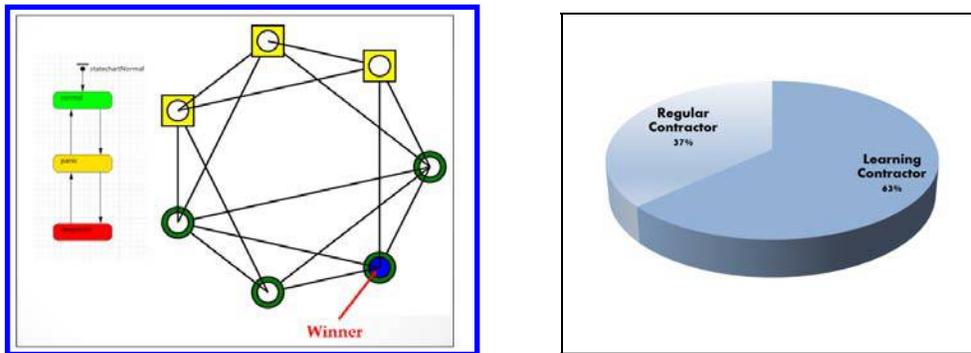

Figure 5. Left: Visual representation of the network, the agents, their states, and the winner at each time step, Right: Pie chart of the winner types after 120 competitions

The results of the simulations indicate that the learning mechanism considerably improved the winning chance of learning agents compared with regular agents. As shown in Figure 5, 67% of the competitions were won by the learning agents. Figure 6 depicts the states of all agents (corresponding to their statechart) at each time step. Since the states on the statechart are linked to the bid gross profit, this diagram clearly demonstrates that throughout the simulation time, regular agents experienced more financial distress. In contrast, learning agents showed a solid performance in generating profit and almost always stayed at the normal state.
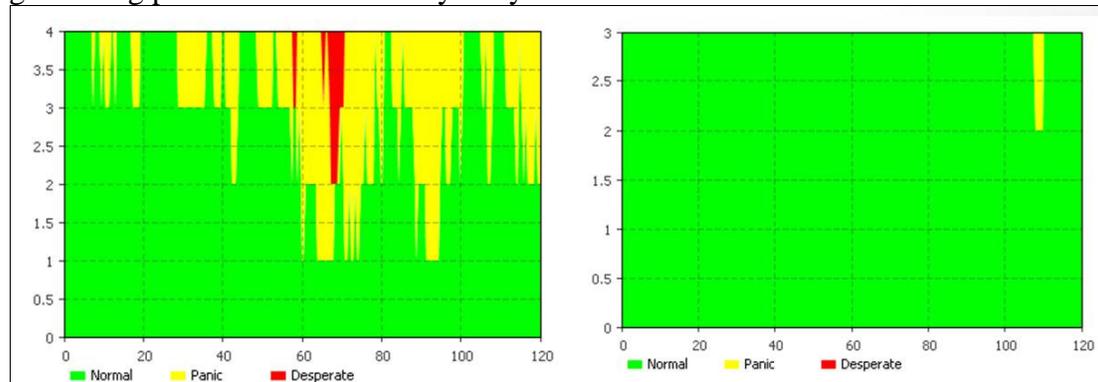

Figure 6. State (normal, panic, or desperate) of all agents at each time step; the vertical axis represents the number of agents and the horizontal axis is time.

Figure 7 shows the project size and the winner's markup at each time step during the simulation. The winner's markup is an emergent property of the system that arises from the complexity of the organizational behavior of each agent as well as the interactions of these agents through business network connections. It is clear that the winner's markup has a volatile behavior. This reflects the agents' adaptation capabilities and consequent changes of strategy. Therefore, the winner's markup will never show a predictable behavior, although it always stays in a reasonable range.
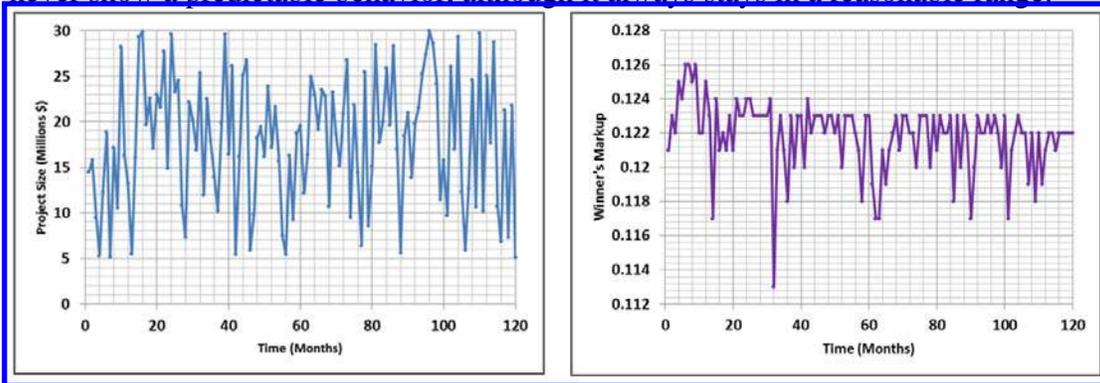

Figure 7. Left: Project size (project cost) generated randomly from a uniform distribution with minimum of five and maximum of 30 million dollars. Right: Winner's markup at each bidding competition.

Additionally, the learning agents have a higher cumulative profit. Cumulative profit is the ultimate metric in the model that gauges the financial performance of contractors. The results of the simulation in Figure 8 show that all of the learning agents have a cumulative profit above 20 million dollars at the end of simulation compared to the less than 19 million dollars cumulative profits of the regular agents.
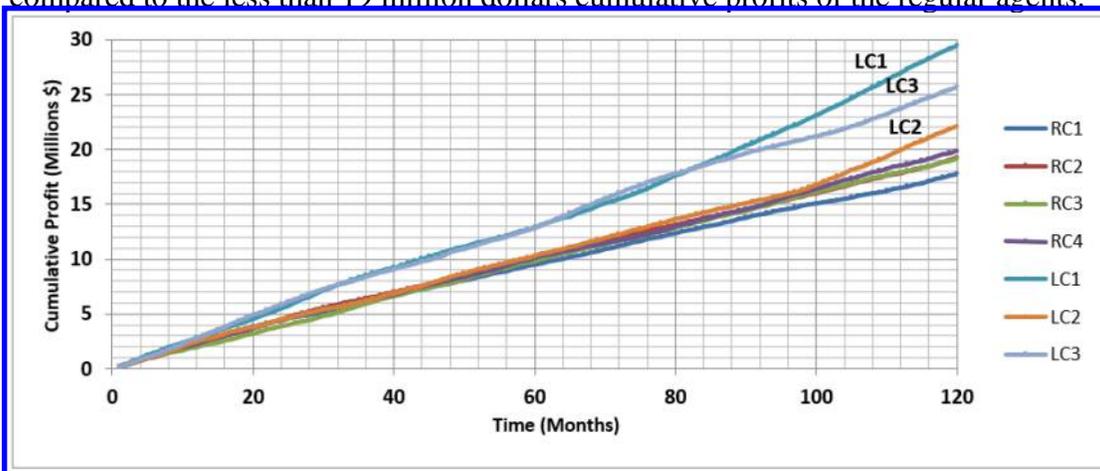

Figure 8. Cumulative profit of all agents in the model throughout the simulation time (RC=Regular Contractor, LC=Learning Contractor).

Three types of analysis were conducted to check the validity of the model output against the expected outcomes. These three analyses are based on the suggestions of Railback and Grimm (2010). Model sensitivity to changes in the key parameter values showed that the outcomes are within a reasonable and expected range. The expected range of the outcomes was calculated by some simplifying assumptions in

Microsoft Excel. We also looked at how uncertainty in the parameter values affected the reliability of the model results. Different random distributions were assigned for some parameters, and all the outcomes were consistently within the expected ranges. Finally, we performed robustness analysis, particularly in response to drastic changes in model structure, such as complete insolvency or unexpected success in early bids.

CONCLUSION

This research aimed to propose a quantitative method for comparing bidding strategies by utilizing adaptive agents. The results of this study show that agent-based simulation is capable of quantifying the effect of adaptive bidding strategies. A preliminary method for capturing the effect of subcontracting network topology on the financial state of a contractor was also examined. Finally, utilization of statecharts in combination with system dynamics proved to be very promising in the modeling of agent behavior and the decision-making process.

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