CONTRACTOR'S BIDDING DECISION MAKING THROUGH AGENT LEARNING: A SYSTEM DYNAMICS MODEL

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ABSTRACT

Competitive bidding is a common method for many contractors to obtain construction contracts. To them, the competitive bidding is fundamentally a decision-making process that is driven by using experiences to insure and maximize expected project profits. This paper describes the learning process in the competitive bidding as a flow of actions including information collection and classification, storing and analyzing, and decision optimization. The paper identifies three basic types of learning process in competitive bidding including individual learning, co-learning, and internal-evaluation. Furthermore, this paper develops an agent-based learning model for bidding decision making using system dynamics. Particularly, two learning algorithms, Park rule and Bayes rule, are modeled and discussed under both individual learning process and co-learning process. Through a dynamic simulation conducted based on the CFMA generic construction firm data, the analysis finds out that learning eventually improves the performance of bidding decisions, even in a situation where competitors also learn.

KEY WORDS

bidding, decision making, learning, system dynamics, simulation.

INTRODUCTION

Competitive bidding is a complex decision-making process with an objective to insure and maximize expected project profits. Two essential decisions in this process include to bid or not to bid decision and the markup decision. Once a contractor decides to bid on a job, he needs to estimate the construction cost and decide an appropriate markup. The markup consists of both job and office overheads, as well as project contingencies and profit. The markup decision is very important to every contractor because it is critical to a contractor's success in winning the job and its subsequent profitability.

Since the early attempts (Friedman 1956, Gates 1967) to answer the question of how the markup size decision should be made, several models have been developed based on the assumption that contractors try to maximize their expected profitability under variable or uncertain profitability of each bidding strategy. These models include the general bidding model by Carr (1982), the average-bid bidding model by Ioannou et.al (1993), and a fuzzy set based bidding decision-making model by Fayek (1998). Park and Chapin (1992)

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summarized the earlier models and presented an algorithm for contractors to develop the optimum bidding strategy. Research attempts have also been made to use multiple criteria or attributes in the determination of bid markup. Seydel and Olson (1990) presented a quantitative method in which three attributes considered in the determination of the optimum bid markup included profitability, risk reduction, and work force continuity. Fayek (1998) also considered new market test as one of the objectives in the markup decision. Lai et al (2002) proposed a multiple attribute decision model including additional criteria called conditional positive profit and the expected positive profit ratio. Admitting the limit of previous models in the availability of the sensitive information about competitors, Mochtar and Arditi (2001) proposed a conceptual model of market-based pricing strategy.

Recent surveys on the bidding practices pointed out that few of these models are used in the construction industry worldwide due to their ignorance of complexity of bidding decisions (Ahmad and Minkarah 1988, Shash 1993, Fayek et. al 1999). One of the most important factors missing in the earlier models is the dynamical learning process that includes the control and adjustment of bidding strategies based on the external environment, business objectives, and past experience. Social systems, especially business organizations, have the capability to change their structures and strategies through adaptations and learning. This capability to learn from internal and external environment gives business organizations, including construction organizations, a constant state of readiness for change and sustains continuous improvement. Therefore, a bidding model with learning capability 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 then presents and a system dynamics based bidding model.

LEARNING IN THE COMPETITIVE BIDDING

LEARNING PROCESS

A classic definition of learning is provided by Tsypkin (1971) in the case of automatic systems as "a process of forcing the system to have a particular response to a specific input signal (action) by repeating the input signals and then correcting the system externally." This procedure is often called supervised learning, where the external correction is performed by a supervisor who knows the desired response to a particular input signal. The corrections are done through reward or punishment that indicates the correctness or incorrectness of the response. There is another type of learning, called unsupervised learning or self-learning, which has no supervisor. Self-learning is a learning method without external corrections (i.e., without punishments or rewards). No information regarding the correctness or incorrectness of the system's reaction is given.

Business organizations involve supervised learning and unsupervised learning. Market usually works as the unique supervisor that drives organizations to learn from lessons, to change old operations, and to survive in changed environments. Business organizations also proactively change processes to adapt to changing environments through developing a learning culture within organizations. The learning culture enables the organizations to evolve itself by creating new knowledge through day-to-day events. In either case, however, when an organization is skilled at creating, acquiring, sharing, and applying knowlodge to improve the performance, it becomes a learning organization (Chinowsky and Molenaar 2005).

Competitive bidding process is also an organizational learning process in which contractors collect and analyze historical bidding information, then develop the optimum bidding strategy. This learning process embodies a flow of actions, including classifying, storing, analyzing, and optimizing (Figure 1). The learning process starts from identifying and classifying useful information into different categories. The identification and classification must depend on criteria that meet the learning objective. In competitive bidding, a contractor could collect related information on job characteristics, number of bidders, contractor's bid price, and bidding results that he believes important to implement the learning process in the competitive bidding. The useful information identified is then stored in such a format that is handy to retrieve and restore, convenient to analyze, and easy to update. The format could be a database or accumulated stocks on a systemetic view. The analysis of the information saved always generates new knowledge about unknowns; for example, the competitor's bidding strategy and how it changes. The knowledge, along with constraints, help to optimize the decision-making in an effort to reach the predetermined target.

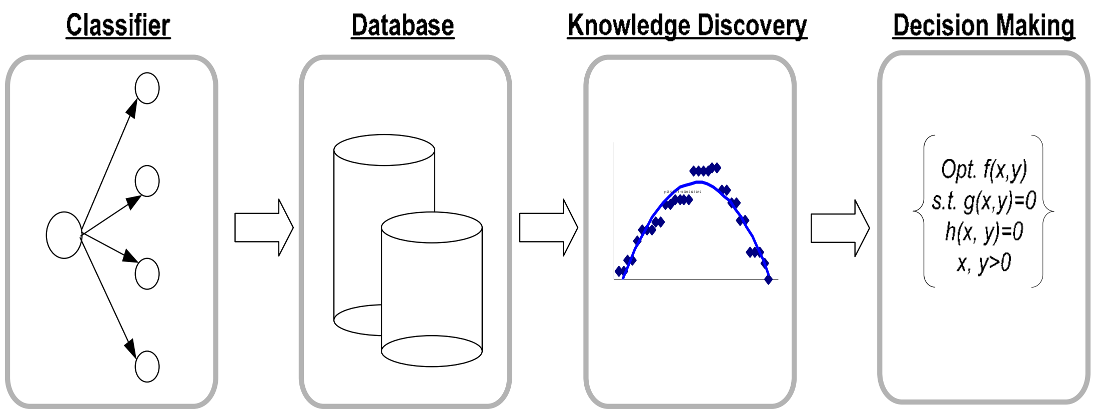

Figure 1 Learning Process in Competitive Bidding

FEEDBACK LOOPS IN LEARNING

Learning in competitive bidding is also a continuous process in which the contractor would bid projects and then adjust the optimum bidding strategy by comparing expected objectives to actual results. The old bidding strategy is translated into an bidding action that in turn results into an updated state of the bidding system. The updated system state then becomes the starting point for the contractor to develop a new strategy. In other words, the learning process involves feedback loops. Prior behavior affects future action. On the other hand, learning in bidding occurs in a competitive environment where one contractor's behavior would affect another's decision and vice versa. When one contractor learns and evolves, his changed behavior drives other contractors to learn and evolve. Therefore, learning in competitive bidding is a multiple-agent system, where an agent is the unit that can learn and change its behavior. Competitive relationships among the learning units constitute the basis of an adaptive bidding system. Therefore, a robust bidding strategy must evolve by learning from the reactions of other agents.

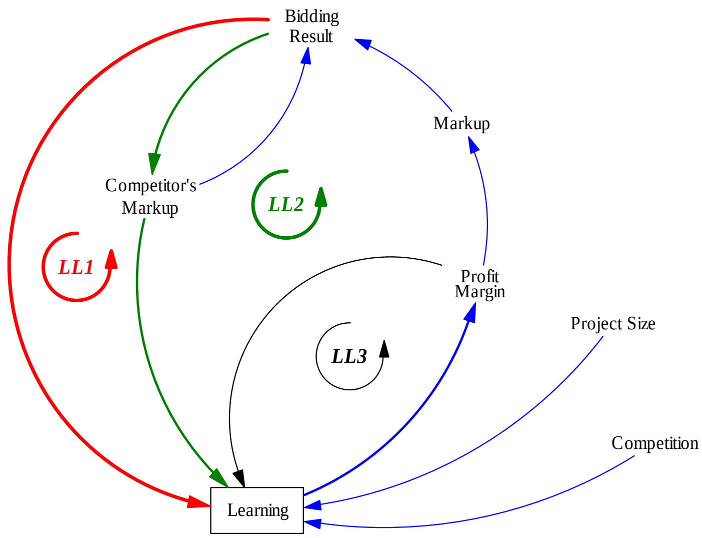

Figure 2 Learning Loops in the Competitive Bidding

Considering the multiple-agent environment where competitors may also tend to adapt the environment, ie. learn from historical data, the learning process encompasses three feedback loops as illustrated in Figure 2: individual learning loop (LL1), co-learning loop (LL2), and internal evaluation loop (LL3). The individual learning loop describes the process whereby the contractor learns from the bidding competition and acquires knowledge about competitor bidding behaviors. Under this learning loop, the agent records the system states, environment variables, and actions of the competitive agent. Then the relationship between the actions of the competitive agent and the system and environment variables is established based on a certain algorithm described in the next section. The relationship is then used to predict the competitive agent's actions that help to reach the optimal agent action. The co-learning loop admits that the competitive agent can also learn from the bidding practices. The competitive agent does the same process and improves his decision-making. However, the competitive agent's learning process is not observable and can only be deduced from his actions and behaviors. In addition to these two loops, the agent may also evaluate the performance of the system by comparing the predicted system state with the actual one, which constitutes an internal evaluation loop.

The combination of the three learning loops constitutes three levels of learning process. The first-order learning only includes the individual learning loop. The implied belief in the first-order learning is that the competitive agent does not learn, which means that competitive agent's action is not determined by the system state. The learning agent could use all historical data to predict competitor's bidding strategty. Finally, the future system state would be predicted through known environment and the learning agent's strategy. The second-order learning combines the individual learning and co-learning loops. Because the competitive agent is also learning, the system state will be determined by the actions of both agents in addition to the known environment. The internal evaluation loop can be merged into either level of learning and constitutes a control on learning. Higher order learning processes can be also identified. If the competitive agent also knows that his learning capability is known, he would also predict the impact of his action under both agents learning. Therefore, he could apply a different strategy, such as pseudo-learning to deceive or mislead the system agent. These learning loops embrace most industry practices in the competitive bidding concerning learning. When a contractor believes that the business environment is relatively static and other bidders continue their strategies, his learning style follows the first order learning process. Likewise, if he finds out competitors continuously improve their bidding behaviors, he would agree that the second order learning process better fits his situation.

LEARNING MECHANISM

Learning mechinism describes the methods and algorithms by which an agent collects and classifies information, creates knowledge, and develops a bidding strategy. It is known that learning is conducted under certain objectives, beliefs, and constraints. Different objective and beliefs may require collecting different information, a different format to save information, a different approach to analyze information and acquire knowledge, and a different method to optimize the actions. If a contractor believes that a competitor's bidding strategy is related to the project size and competition (measured by the number of bidders), he may collect relative information on the project size, the number of bidders, and the competitor's bid price and categorize and store the bid price into several sections according to project sizes and number of bidders. Then he could analyze the distribution within each group and optimize his strategy based on the estimated distribution. If he further believes that competitors might also change their strategies because they also learn and react to his action, he will need to collect necessary information and develop a mental model to identify whether the competitors have changed their strategies.

There are two basic learning mechanisms in competitive bidding, Park rule and Bayes rule. In the Park rule, it is believed that project characteristics including the number of bidders and the job size determine a contractor's optimum markup (Park and Chapin1992). The contractor would learn to identify how the competitors determine their bid price and thereby establish his own bidding strategy. Therefore, information regarding the variables of a competitor's markup are identified and classified into different zones that are divided based the range of the variables. Within each zone, it is believed that an optimum risk-adjusted markup exists. The learning is to analyze the competitor's markup in each zone and to seek the optimum markup size under certain constraints. On the contrary, Bayes rule assumes that the contractor's markup strategy is predetermined in accordance with the competition level (Cui 2005). The contractor would learn to identify the competition level through bidding practices. Therefore, the related information is classified and saved relating to the variables affecting the competition condition. The probability of each competition level is estimated by computing the posteriori probability from prior probability, which means that earlier knowledge becomes prior and used to compute the new knowledge based on new information available. This paper uses system dynamics to model two learning mechanisms in the first-order and second-order learning loops.

SYSTEM DYNAMICS MODEL

SYSTEM DYNAMICS APPROACH

System dynamics was introduced by Forrester (1961) as a method for incorporating dynamic features into complex systems, particularly an industrial context. It has been used to examine various social, economic, and environmental systems, where a holistic view is important and feedback loops are critical to understand the interrelationships. During the past ten years, research efforts have been made to use system dynamics in construction projects and construction organizations (Ford and Sterman 1998, Park and Pena-Mora, 2003, Ogunlana et al. 2003). The system dynamics approach focuses on the system behavior over time. The dynamic behavior is determined by the system structure that is described in the system dynamics as cause-effect relationships with stock variables, flow variables, and feedback loops. Stock variables are accumulations. They characterize the state of the system and provide it with memory and inertia. Flow variables are rates that alter stocks over time so that alter the state of the system. The readers are referred to Senge (1990) and Sterman (2000) for detailed explanation of the system dynamics. The system dynamics use a particular graphic notation. Stocks are represented by rectangles. Flows are represented by a pipe pointing into/out of the stock. This paper uses Vensim PL version 5.4 to model and simulate a learning based bidding system.

PARK LEARNING RULE

To develop the optimum markup under Park learning rule, historical projects are broken down into different small groups according to the size and number of bidders. It could become detailed when additional criterion is considered and the strategy is broken down into more details. This definitely leads to a more accurate learning result. However, by doing that, the learning process becomes more complicated and more historical project data are needed to make reliable results because of the increase in the number of groups. Without losing the thought of the Park learning rule, this study assumes two criteria and two groups for each criterion.

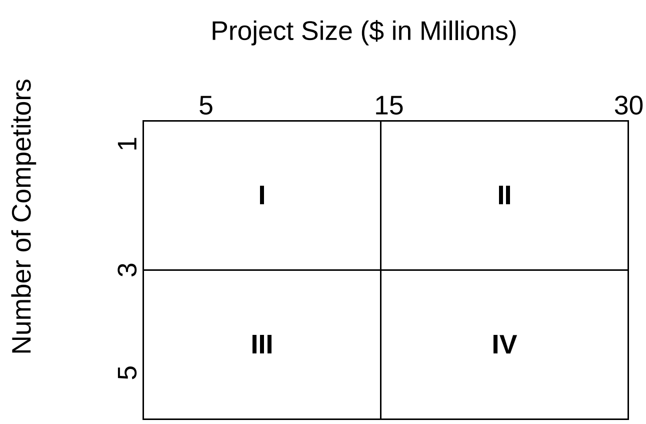

Figure 3 Data Classification under Two Criteria

The bidding agent learns the competitive agent's bidding strategy through collecting and analyzing historical project and bidding information. The competitive agent represents the lowest competitor who may not be the same bidder all the time. The information is recoded and classified into different zones by a module called the classifier. The classifier works in such a way that the collected data are categorized according to predetermined criteria which, in this case, are job size and number of competitors. Four small zones are identified and named zone I, II, III, and IV, where zone I indicates small projects under low competition, II large projects under low competition, III small projects but high competition, and IV large projects under high competition (Figure 3)

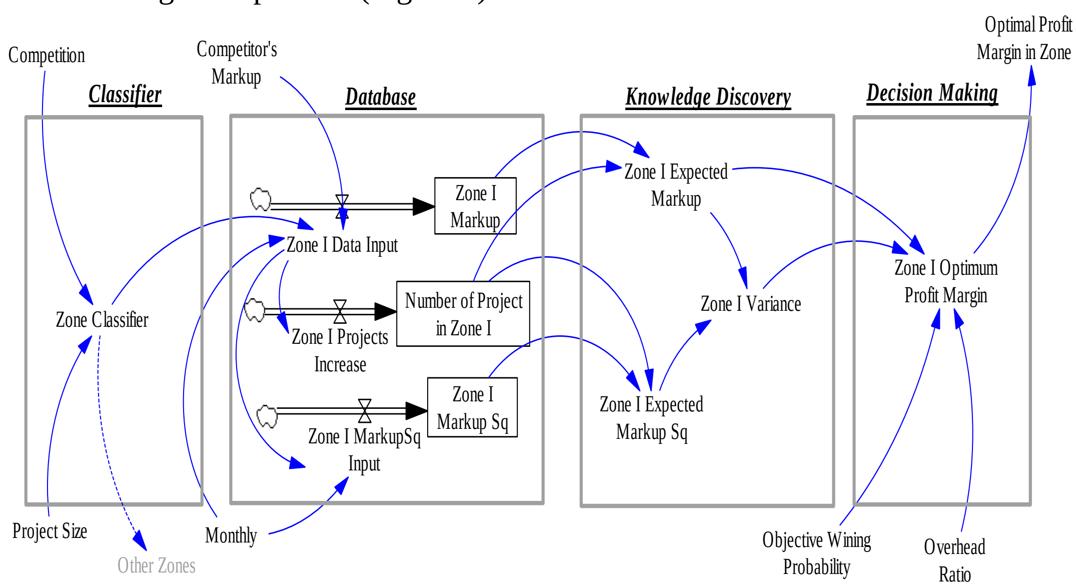

Figure 4 Park's Rule Learning Mechanism

It is assumed that the competor's markup size within each zone follows a probability distrubution. Under the first order learning process, the competitor does not learn so his bidding strategy keeps same all the time. The probability distribution of the competitor's markup maintains the same parameters at any time point and the competitor's action has no impact on the parameters. Unbiased, sufficient, and consistent statistics about the parameters of a normal distribution are the sample mean and sample variance, where the sample includes all historical data. To estimate the sample mean and variance of a historical competitor's markup, the number of projects in zone I and the markup square value have to be stored in addition to the markup size at any time. Whenever a project meeting the criteria of zone I is identified by the classifier, the competitor's markup and its square value will be stored in two stock variables. And the number of projects in zone I will increase by one (Figure 4). With the saved data, the sample mean and variance can be calculated as the unbiased estimators of the mean and variance of the competitor's markup.With the knowledge of the estimated mean and variance of the competitor's markup, the agent can determine the optimum bidding strategy. If a contractor strives to improve the winning ratio from 30% to 50%, his strategy is to take a markupo at μ_I, or profit margin at (μ_I-*overhead*). In this case, his markup (thus bid price) will be lower than the competitor's at a probability of 50%. This is called the *Zero*

Sigma Strategy. If he applies the *Positive Half Sigma Strategy* (or markup at $\mu_I - 0.5 * \sigma_I$), the winning probability increases to 69%.

BAYES LEARNING RULE

Under Bayes learning rule, historical information is first classified according to the competitor's markup. For instance, the projects with lower than 5% markup are categorized into the Low Markup group. Otherwise, they belong to High Markup group. Then the data regarding the number of competitors, job size, and number of projects in the group are stored in stock variables, which are used to estimate the mean and standard deviation (SD) of these variables within each group. Furthermore, the estimated mean and SD constitute a prior probability of the groups. With new data on the project size and the number of competitors, the prior probability is used to calculate the likelihood or posteriori probability based on Bayesian Theory. It is obvious that the steps in the Bayes rule learning are interdependent and are combined into Bayes decision theory (Cui 2005).

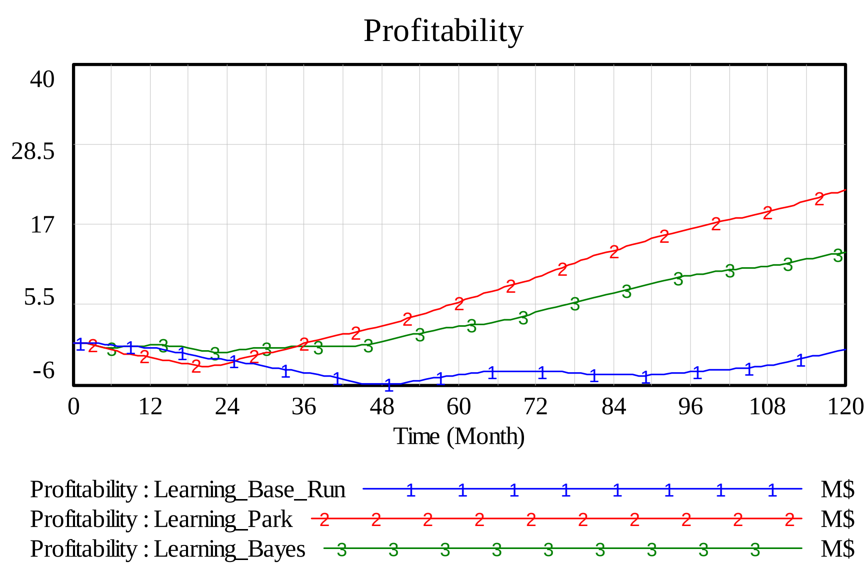

Figure 5 Comparison of Learning Algorithm

SIMULATION AND DISCUSSION

INDIVIDUAL LEARNING

The model was simulated with the data from annual financial survey conducted by Construction Financial Management Association in 2002 (CFMA 2002). The financial statements for averaged company were used to represent a generic construction company with total assets around 13 million dollars. A similar size civil contractor in Indiana was interviewed to obtain other non-financial data including distribution of project sizes, average duration, and range of competitor's markup. The Vensim system dynamics software package was used to simulate the behavior of the bidding system for 10 years.

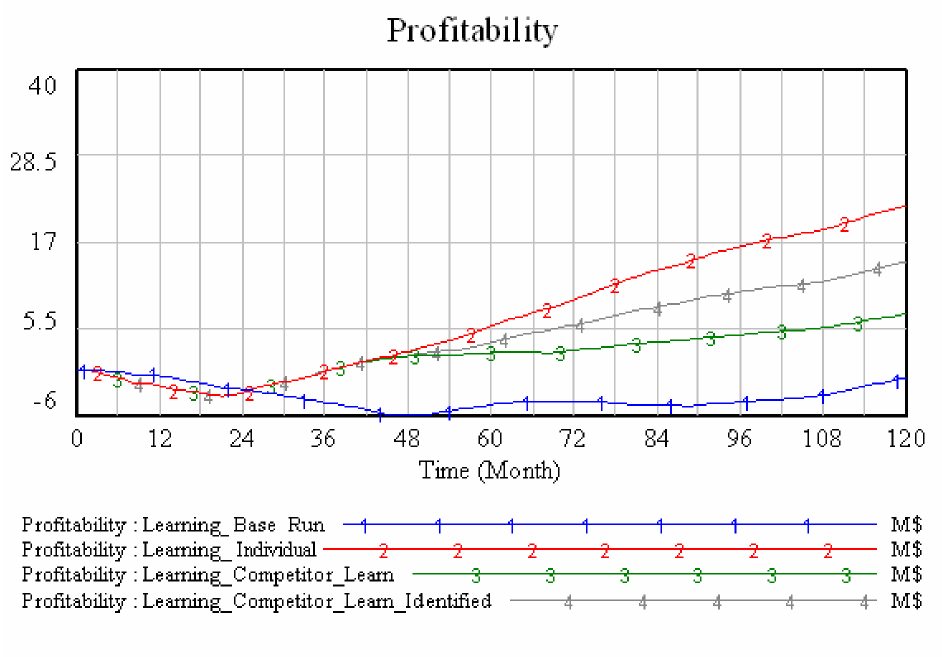

Figure 6 Learning under Competitor's Learning

The study finds out that learning does improve the performance of the bidding strategy. In other words, learning increases the winning ratio, thus improving the profitability of the system. As compared to the base run (curve 1 in Figure 5), both learning rules (curve 2 and 3) improve the performance of the bidding system significantly. The explanation for this improvement could be due to the reduction of uncertainties. Under the base run, the contractor knows very little about the competitor's strategy. Therefore, his bidding decision does not depend upon the competitor's strategy. When random noise causes small changes, small changes can amplify. If the contractor learns from the experience, he will know the distribution of the competitor's markup. In this example, the mean and variance of the competitor's markup are obtained from learning. The knowledge is used in the decision of bidding markup. A better performance is foreseeable.

SECOND ORDER LEARNING: WHEN COMPETITOR ALSO LEARNS

The simulation was also conducted under the co-learning environment. Under co-learning , the agent must consider the change of the other agent's strategy due to the competitive agent's learning. However, it is not observable whether or not the competitive agent learns. Therefore, the agent has to identify the change through an observation on the reaction of the competitive agent. The contractor could observe a series of new competitor markups and test whether the statistical parameters are different from the original estimated parameters. On the other hand, he could set a trigger that indicates a change of a competitor's strategy. Figure 6 demonstrates the simulation results under different scenarios. Curve 1 indicates the profitability behavior under the scenario of no learning. Curve 2 shows the scenario of indivual learning under Park Rule. Curve 3 is the scenario where the competitor learns but is not identified. The curve 4 represents that both agents learn and the contractor has an identifier to alert for change in the competitor's bidding strategy. It shows that competitor learning worsens the profitability of the contractor, however, if the contractor is able to identify the change, performance can be improved.

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