Construction Bidding and the Winner’s Curse: Game Theory Approach

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Abstract: In the construction industry, competitive bidding has long been used as a method for contractor selection. Because the true cost of construction is not known until the completion of the project, adverse selection is a major concern. Adverse selection is when the winner of the contract has underestimated the project’s true cost. Thus, the winning contractor will most likely earn negative or at least below normal profits. The winner’s curse is when the winning bidder submits an underestimated bid and is thus cursed by being selected to undertake the project. In the multistage bidding environment, where subcontractors are hired by a general contractor, the winner’s curse may be compounded. In general, contractors suffer from the winner’s curse for a variety of reasons including inaccurate estimates of project cost; new contractors entering the construction market; minimizing losses in case of recession of the construction industry; strong competition within the construction market; differential opportunity costs, which can affect the behavior of contractors; and the intention to win the project and then remedy the losses through change orders, claims, and other mechanisms. Using a game theory approach, this paper aims to analyze—and potentially reduce—industry exposure to the effects of the winner’s curse in construction bidding. To this end, the authors identify the degree of the winner’s curse in two common construction bidding environments; namely, single-stage bidding and multistage bidding. The objective is to compare the aforementioned two construction bidding environments and determine how learning from past bidding decisions and experiences can mitigate the winner’s curse. To this end, and through defining the relationship between the construction bidding and auction theory, the authors utilized a three-step research methodology that involved (1) presenting the symmetric risk neutral Nash equilibrium (SRNNE) as an optimal bid function; (2) developing simulation models for single and multistage construction bidding processes; and (3) analyzing the results of the simulation models, which is based on an actual dataset of projects provided by the California Department of Transportation. This research demonstrated that the majority of general contractors and subcontractors suffer from the winner’s curse in both single-stage and multistage bidding environments. Moreover, from a winner’s curse perspective, the multistage bidding environment incurs more losses than the single-stage bidding environment. However, through learning from past experiences, the multistage bidding environment provides contractors with a better opportunity to avoid the winner’s curse if compared with the single-stage bidding environment. This research should be beneficial for the profession to better understand the bidding decision-making processes. For future work, cooperative game theory can be applied with the integrated project delivery principles to help all associated parties mutually achieve their project objectives. DOI: 10.1061/(ASCE)CO.1943-7862.0001058. © 2015 American Society of Civil Engineers.

Author keywords: Contracting.

Introduction

Understanding the basic processes within the construction industry is essential for contractors to remain competitive, and also for a nation’s economy to operate effectively and efficiently. According to Kululanga et al. (2001), the construction industry incorporated simple and straightforward processes in the early years. However, the construction industry is getting more complex and sophisticated in today’s world. The growth of the construction industry has developed a competitive environment for contractors. Consequently, contractors need to create well-developed plans that incorporate different perspectives in order to stay ahead of competitors. One of the difficult tasks in the construction industry is the contractor selection process. Competitive bidding has long been used as a method for allocating contracts (Seydel 2003). Moreover, in the public sector, competitive bidding has been considered as a legal requirement. Therefore, it is argued that one of the main factors that have a great effect on the success of construction projects is the firms’ bidding strategies.

According to Park and Chapin (1992), contractors submit their proposals to show their desires to carry out a construction project for an agreed price. Generally, in the construction bidding process, submitted bids are evaluated technically, and then the technically approved bids are evaluated financially or based on the submitted price. For the financial evaluation of the submitted bids, there are many methods such as the low bid method, the second lowest bid method, the average bid method, and the below average bid method (Ioannou and Awwad 2010). According to Ioannou and Awwad (2010), the low bid method is the most common method for
As noted by Gates (1967), there are many reasons for a contractor to construct the project based on the agreed price and schedule, and the contractor who is technically approved and has the lowest price among which is applied in this paper, the contract is awarded to the contractor. In the low bid method, every contractor is making many critical decisions corresponding to desire winning the project contract, such as (1) increasing earned profit, (2) minimizing losses because a contractor must keep the firm intact even during recession periods, and (3) minimizing the profits of competitors in order to maintain a long-term good competitive position within the construction industry market.

Due to all the aforementioned reasons, before submitting a bid every contractor is making many critical decisions corresponding to each bidding situation. As noted by Bagies and Fortune (2006), in the stage before committing to a construction project, the contractor’s decision is affected by (1) the bid or no bid decision, in which the contractor considers many factors that would help in determining the expected benefits from a construction project and correctly evaluating it, and (2) the markup decision, which is related to the bidding strategy. As quoted by King and Mercer (1985), the bidding strategy is an important part of the overall business planning of any construction company. Over the last 50 years, many models have been developed for the application in the construction bidding. According to Wanous et al. (2000), the majority of these bidding models have focused only on the markup decision, such as the models developed by Friedman (1956) and Gates (1967).

However, despite the many publications related to construction bidding, the bidding models largely ignore human behavior (Ahmad and Minkarah 1988). Many researchers argued that in reality, the bidding decisions are based on experience and intuition and influenced by the emotional responses toward the pressures of each bidding situation (Fayek 1998). Moreover, Runeson and Skitmore (1999) argued that some basic assumptions, which were applied in the developed bidding models, are not realistic and their predicted results are not always correct. Thus, the need for a more efficient bidding model to be used in construction bidding is obvious, which matches the realistic situation of the construction bidding process in its assumptions and overcomes the limitations of the previously published bidding models. More recently, many researchers have tended to develop new techniques to aid contractors in rendering their bidding decision utilizing fuzzy neural networks (Polat et al. 2014). It is anticipated that these techniques should aid contractors in estimating the optimal bid amount to submit in a construction bidding situation.

Finally, construction projects face a high level of uncertainty of numerous events that may occur during the construction project’s lifecycle. For instance, contractors contend with inevitable and unforeseen increase of input cost, labor issues, and construction conditions that must be accounted for when developing a bid for a long-term project. At the time of submitting bids, contractors cannot know with certainty the actual project construction cost. As such, the construction industry relies on estimates of the project cost based on the contractors’ current information, past experience, and utilizing methods such as RSMeans. Thus, in construction bidding, contractors who underestimated project cost and bid less than the realized project construction cost face the problem of adverse selection. Adverse selection results in what is known as the winner’s curse.

Goals and Objectives
Using a game theory approach, this paper aims to analyze—and potentially mitigate—the effects of the winner’s curse in construction bidding. To this end, the authors identify the degree of the winner’s curse in two common construction bidding environments; namely, single-stage bidding and multistage bidding. The objective is to compare the aforementioned two construction bidding environments and determine how learning from past bidding decisions and experiences can mitigate suffering from the winner’s curse.

Background Information

Game Theory
Since the publication of Theory of Games and Economic Behavior in 1944 by John von Neumann and Oskar Morgenstern, social and behavioral sciences have developed mathematical tools to describe human behaviors. To this end, game theory is defined as “the study of mathematical models of conflict and cooperation between intelligent rational decision-makers” (Myerson 1991). Game theory has been applied to different aspects of human life. In the 1950s and 1960s, game theory was applied in battle filed decisions and political problems. In the 1970s, game theory revolutionized the field of economic studies. Moreover, it has been applied to sociology, psychology, and biology. Game theory and its practitioners received a long awaited recognition and legitimacy in science after the awarding of the Nobel prize to John Nash, John Harsanyi, and Reinhard Selten in 1994 (Turowy and Stengel 2001).

In the construction industry, researchers have applied various game theoretic models to explain and predict outcomes. Ho (2001) utilized game theory to analyze build-operate-transfer project procurement processes in the presence of asymmetric information and its effect on project financing and government policy. Drew and Skitmore (2006) analyzed competitive bidding schemes in the construction industry by means of auction theory, a subdiscipline of game theory. Ho and Liu (2004) analyzed the dynamics between contractors and owners in construction claims through a game theoretic model. Karl (2014) developed a module-oriented modeling approach to be used in the simulation of multicasual and dynamic relationships on different levels of the construction industry. In addition, game theory has been also applied to examine strategies for subcontractor selection (Unsal and Taylor 2011) and to analyze the effect of bid compensation on the competitive bidding process (Ho 2005). Thus, game theory has been considered an important tool to analyze many issues in the construction industry.

In general, game theoretic models can be classified according to information completeness and the way in which games are played. Based on the way of playing the game, there are two types: (1) static games, in which players make decisions and take actions simultaneously, without knowing the decisions chosen by other players, and (2) dynamic games, in which players make decisions and take actions sequentially, with the observation of other players’ actions (Ho and Hsu 2014). Generally, the construction competitive bidding model can be considered to follow the static game concept because bidders do not know bids of their rivals at the time of submitting their bids.

Moreover, there are basically two main branches of game theory concepts: (1) cooperative game theory, in which players cooperate together to get more benefits for each and allocate the gains fairly between them, and (2) noncooperative game theory, in which each player selects a strategy independently and tries to maximize the payoff, and there is no collusion between the players (Asgari and Afshar 2008). Nash (1950) equilibrium is considered as the
solution to noncooperative games under the assumption that all players are rational. Generally, construction competitive bidding can be described as a noncooperative game because each general contractor (GC) or subcontractor (SC) is trying to win the competition and maximize the individual’s payoff in the presence of conflict of interest. Thus, it can be concluded that to develop a better model that describes construction bidding in reality, the game theoretic model shall be noncooperative with static moves and incomplete information.

### Construction Bidding and Common Value Auctions

Auctions have been used to distribute goods and services for thousands of years. From the perspective of game theory, auctions are considered one of the most outstanding applications of games with incomplete information because participants in auctions have different private information, which is the main factor affecting their strategic behavior. Auctions are typically classified into two major types: (1) private value auctions, and (2) common value auctions. In a private value auction, the bidders know their own value of the item being auctioned with certainty, but they do not know other bidders’ values. However, in a common value auction, the item being auctioned has the same value (i.e., cost) to everyone, but none of the bidders know this value with certainty. As such, each bidder develops an independent and identically distributed estimate about the true value, and the winner is the one having the most pertinent information to such true value (Kagel and Levin 2002). In relation to the construction industry, contractors have two sources of incomplete information at time of submitting their bids: (1) actual (realized) project construction cost, and (2) their competitors’ estimates of the project construction cost. Thus, according to Dyer and Kagel (1996), construction bidding is considered as a common value auction. This is due to the unknown true cost of construction projects, which cannot be realized with certainty until completion of the project. Furthermore, bidding for construction contracts is referred to as a reverse auction. Unlike auctions for the purchase of goods and services, construction auctions are for the sale of goods and services. In such a setting, the auctioneer determines the winner as the bidder submitting the lowest bid, based on the low bid method, rather than the highest bid to purchase an item.

### Winner’s Curse

According to Kagel and Levin (2002), the story of the winner’s curse was first introduced by Capen et al. (1971). The three petroleum engineers claimed that oil companies had suffered unexpectedly low rates of return in early outer continental shelf (OCS) oil lease auctions. Thereafter, researchers have recognized the influence of the winner’s curse in auctions for publication rights (Dessauer 1981), corporate takeover battles (Roll 1986), real-estate auctions (Ashenfelter and Genesore 1992), and cattle auctions (Coatey et al. 2012).

Particularly to the construction industry, the winner’s curse can be defined as the situation when the bidder, with the most optimistic (low) project cost estimate, wins the project contract based on a submitted bid less than the true project construction cost. Such a bidder, who fails to take the winner’s curse problem into account, will most likely earn negative or, at least, below normal profits.

According to Dyer and Kagel (1996), U.S. general construction contractors usually utilize one of the following three mechanisms to avoid the winner’s curse:

- One mechanism is that most states’ laws allow low bidders to withdraw their bids for public projects in case of arithmetic errors, and without being subjected to penalty. The meaning of arithmetic errors is broad and not well defined, and contractors can benefit from this to escape from the winner’s curse by withdrawal of their submitted low bids.
- The second mechanism depends on the relationship between general contractors and subcontractors. A general contractor can bid higher, benefiting from the low submitted bids by the subcontractors in lowering the joint submitted bid and reducing the likelihood of suffering from the winner’s curse.
- The third mechanism is change orders. Change orders refer to situations in which clients or owners adjust the original scope of construction of the project after signing the contract. Usually, the price of a change order is established through negotiations between associated stakeholders. Through tough negotiations, a general contractor who underbids a project can recover at least some losses, and in some instances, make some profit.

Generally, the aforementioned mechanisms are considered ineffective, especially the third mechanism of change orders due to its disadvantage of resulting in an adversarial relationship between the subcontractor and general contractor, and client, as well as potential legal costs. Therefore, in order to avoid the winner’s curse, and due to the relative ineffectiveness of the aforementioned mechanisms, contractors must carefully consider all factors while preparing their bids such as market factors as location of the project, number of competitors, and time, and project factors such as its size, type, and scope. Being the case, the following section discusses the symmetric risk neutral Nash equilibrium (SRNNE) bid function as a potential tool for optimal strategic bidding that could avoid the winner’s curse.

### SRNNE Bid Function

Wilson (1977) developed the first Nash equilibrium solution and later, Dyer et al. (1989) presented the SRNNE for a first price sealed-bid common value auction, in which bidders independently submit their bids in a closed auction and the winner is the one who has submitted the lowest bid value. Furthermore, Dyer et al. (1989) utilized this optimal bid function to analyze a series of laboratory experiments in which bidders competed for the right to supply an item of unknown cost such as construction contracts.

Dyer et al. (1989) focused primarily on analyzing and comparing the behavior of experienced executives in the construction industry with inexperienced students. The authors conducted four experiments; three of those experiments employed University of Houston upper-level economics majors students with no prior laboratory experience, while Experiment 4 employed executives from the local construction industry. Each experiment consisted of different auction periods in which the right to supply was awarded to the low bidder. The presumption was that experienced bidders would not fall prey to the winner’s curse to inexperienced bidders. Interestingly, the authors found that both inexperienced students and experienced executives were almost similar in suffering from the winner’s curse. Furthermore, the authors studied the effect of increasing numbers of bidders on their behaviors. Dyer et al. (1989) argued that in a common value auction, there are two forces when the number of bidders is increased. Those two forces were referred to as a strategic force and item valuation considerations. The strategic force leads to lower bidding with increases in the number of bidders because the probability of winning with a higher markup decreases. On the other hand, item valuation considerations lead to higher bids because the adverse selection problem (winner’s curse) increases with increasing in the number of bidders. Therefore, in order to avoid the winner’s curse, the SRNNE bid function requires that bids be constant or increasing with increasing in the number of the bidders. Based on the results of the conducted experiments,
Dyer et al. (1989) found that both categories of inexperienced students and experienced executives suffered from increased losses with increases in the number of rivals, which implies that bidders were responding in the wrong direction and affected by the strategic force or were not responding sufficiently in the right direction. Ultimately, the authors concluded that the winner’s curse mainly depends on the market size, auction form, and subject population.

The description of the SRNNE is as follows: let the actual cost of construction project \( C^* \) be unknown at the time of submitting bids. The bidder \( I \) who wins the construction project contract will earn a profit that is equal to the difference between \( I \)'s bid \( B_i \) and the actual cost of the project \( C^* \), as shown in Eq. (1), where \( c_i \) is the contractor’s initial estimated cost (i.e., bidding value)

\[
\text{Profit}_i = B_i - C^* \tag{1}
\]

In deriving the SRNNE optimal bid function, the actual cost of the project \( C \) is assumed to be drawn from a uniform distribution on \([X_1, X_2]\). Furthermore, each bidder receives a private signal \( c_i \) about the true cost. This private signal is assumed to be randomly drawn from a uniform distribution on \([C - \epsilon, C + \epsilon]\). The variable \( \epsilon \) represents the range of private signal around the true cost and depends on the accuracy of the bidder’s estimate. Moreover, it is also assumed that the uniform distributions of the actual cost \( C \) and the number of bidders \( N \) are common knowledge to all participating bidders, while each bidder privately knows his private signal \( c_i \) and as a function of \( \epsilon \). The SRNNE optimal bid function, derived by Dyer et al. (1989), in the interval \([X_1 + \epsilon < c_i < X_2 - \epsilon]\) is as follows:

\[
b_i(c_i) = c_i + \epsilon - Y \tag{2}
\]

where \( Y = [2\epsilon/N + 1] \exp[-(N/2\epsilon)(X_2 - x - c_i)] \). The \( Y \) term diminishes rapidly as \( c_i \) moves below \((X_2 - \epsilon)\). Also, the SRNNE implies that signals are marked up by a value equal to \( \epsilon \) to avoid the winner’s curse. It is logical that if bids are based only on estimating the project cost close to \((X_1 + \epsilon)\), the bidder will earn, on average, negative profits.

**Research Methodology**

After defining the relationship between the construction bidding and auction theory, the authors utilized a three-step research methodology that involves: (1) presenting the SRNNE as an optimal bid function; (2) designing and developing simulation models for single-stage and multistage construction bidding processes; and (3) analyzing the results from the simulation models, which are based on an actual data set of California Department of Transportation projects. The main purpose is to analyze the bidding behavior of general contractors and subcontractors. Moreover, the authors aim to examine the effect of the nature of construction bidding environment (single-stage bidding versus multistage bidding), as well as learning from past experiences, on the degree of the winner’s curse experienced.

Generally, the simulation model consists of a single-stage bidding game (SSG) and a multistage bidding game (MSG). The model is implemented twice. First, the agents (general contractors and subcontractors) choose their bids randomly (i.e., random bidding model). Second, a learning module is integrated into the random bidding model (i.e., experience-based bidding model) in order to analyze the effect of the learning in regards to the agents’ bids decisions. For modeling purposes, in each round in both models each contractor would be given a different private signal, which represents the contractor’s estimate of the true cost of the project, and the value of the variable \( \epsilon \), which would be divided into six equal fragments above and below the given private signal. As such, each contractor has 13 values to choose from for the submitted bid in each round.

In the experience-based bidding model, the learning module is following Roth-Erev reactive reinforced learning (Erev and Roth 1998), in which the used decision variable and the achieved reward (positive or negative) are determined according the following plan shown in the following equations:

\[
\text{Contractor action’s propensity: } q_j(t + 1) = q_j(t)[1 - \mathcal{O}] + E_j(k) \times (1 - \alpha) \tag{3}
\]

\[
\text{Contractor action’s probability: } p_r_j(t) = q_j(t) / \sum q_j(t) \tag{4}
\]

where \( q_j(t) = \text{propensity of action } j \text{ in time } t; \ p_r_j = \text{probability distribution of action } j; \ \mathcal{O} = \text{forgetting parameter; and } \alpha = \text{experimenting parameter. Both } \mathcal{O} \text{ and } \alpha \text{ allow the contractor to explore more actions in the next rounds based on the earned rewards. Thus, following Roth-Erev reactive reinforcement learning, the experience-based bidding model can change the propensity of the decision variables, and correspondingly their selection probabilities based on the earned reward as shown in the following equation:}

\[
E_{jk} = 0 \tag{5}
\]

where \( E = \text{reward for the } j \text{ available action given the action taken in the } k \text{th round. In case } j = k, E \text{ will be either } +1 \text{ or } -1 \text{ based on whether the project contract is won or not, respectively, and } -2 \text{ if the contract is won with a submitted bid less than the true cost of the project.}

**Design of the Single-Stage and Multistage Bidding Games**

In the SSG, as shown in Fig. 1, there are only three general contractors competing to win a similar project contract in each round. The contract is awarded to the general contractor that submits the lowest bid.

Alternatively, in the MSG, as shown in Fig. 2, there are three general contractors. Each general contractor receives bids from three subcontractors for a symmetric part of the project. In the MSG, it is assumed that the general contractor subcontractors up to 30% of the project work based on the low bid method. Thereafter, the three general contractors compete against one another to win the project by submitting their joint bids to the owner. Finally, the contract is awarded to the lowest of the three submitted joint bids by the general contractors, and consequently the winning subcontractor wins the project contract.
The projects in the SSG are designed to be the same as those in the MSG in order to facilitate direct comparison between the two bidding game settings.

**Basic Assumptions and Considerations**

In order to reduce the variability and facilitate the comparison between the two game types (SSG and MSG), there are some basic assumptions and considerations for each game type in each round. Those assumptions serve as the rules for the simulation model, which are as follows:

- At each round in both SSG and MSG, each subcontractor and general contractor is given a different private signal, which represents the estimated true construction cost of that person’s part in the project.
- The simulation model is designed such that, at each round in both SSG and MSG, the contractors would choose a random bid within the range of $\epsilon$, which is shown afterward in Table 1, around the given private signal for the random bidding model or utilizing the learning module for the learning model.
- In both SSG and MSG, there are six project categories and each category is represented by 15 projects.
- The true cost of the project is considered unknown for contractors at the time of submitting their bids, and it is based on some actual California Department of Transportation projects.
- In case of the learning model, for simplicity, it is assumed that the contractors would learn from their past bid decisions within the same category, and start over in the next category.

For example, for general contractors who are bidding for one of the projects in Category 1 in the SSG, the true cost is assumed to be randomly drawn from a uniform distribution with the range of $25,000 to $50,000. Furthermore, the private signals are randomly drawn within $750, which represents the value of $\epsilon$, around the true cost. This implies that, at each round, the true cost of the project would be within $\pm 750$ around the private signal. Fig. 3 illustrates the distribution of the private signals and the true cost at a round for in Category 1 in SSG as an example.

**Simulation Model Data Set**

As previously mentioned, the simulation is implemented using some data set, which is based on real projects conducted by the California Department of Transportation, to simulate the construction bidding process in reality. In both SSG and MSG, the projects are divided into six categories based on the true cost of the project. Each category is represented by 15 projects in each game type in the simulation model. Furthermore, the value of $\epsilon$ is different from one category to another in order to maintain a reasonable degree of accuracy of contractors’ estimates in reality. Based on a review from experienced individuals in the construction industry, the value of $\epsilon$ is assumed to be equal, on average, to 2% of the project true cost in each category. The number of bidders $N$ is assumed to be always equal to three in each bidding situation, either between subcontractors or general contractors, as shown in Figs. 1 and 2. In addition, $X_1$ and $X_2$ refer to the upper and lower boundaries of the true costs in each of the project categories. Table 1 shows the six categories and the value of $\epsilon$ for each category.

The simulation model of the single-stage bidding game and multistage bidding game was implemented on NetBeans IDE 7.4 platform using Java programming language.

**Results and Analysis**

**Results of the SSG and MSG of the Random Bid Choice Model**

In the single-stage bidding game, based on the results of the conducted simulation model, it was found that in 75 out of the
In the multistage bidding game, the results indicated that the winning general contractor suffered from the winner’s curse in 83 out of the 90 projects, representing approximately 92% of the projects. Additionally, the winning general contractors suffered the winner’s curse in 77 out of the 90 projects, representing approximately 86% of the projects.

Therefore, the results indicate that the winning general contractors are able to avoid the winner’s curse more often than the winning subcontractors. This result is consistent with Dyer and Kagel (1996) in that the general contractors benefit from the low subcontractors’ bids, which aid in lowering the required joint bids to win the project contract and mitigate the likelihood of suffering from the winner’s curse.

Moreover, the results indicated that in the MSG all the projects—except one project—in which the winning general contractors earned some profits (i.e., 13 projects), their corresponding winning subcontractors suffered from the winner’s curse. Therefore, it is important to highlight that based on the characteristics of the construction competitive bidding and noncooperative game theory, in the MSG each of the winning subcontractors or general contractors is considered liable to the submitted bid for the subcontractor’s or general contractor’s part of the project. In other words, the party suffers some losses in the part of the project considered liable to them, while the other will earn the profits based on the submitted bid for the other’s part of the project.

Overall, in the MSG, based on the low bid method, a general contractor must submit a joint bid less than the joint bids submitted by his competitors in order to win a project contract. In preparing the joint bid, a general contractor considers the bid of the winning subcontractor plus the bid prepared for the general contractor’s part of the project. Based on the overall results of the conducted random bid choice model from the MSG, it was found that in 85 out of the 90 projects, the winning joint bid is less than the joint true cost of the project, which represents approximately 94% of the projects. Despite that, in some projects either the winning subcontractor or general contractor made positive profits because of the high losses on one of their parts. Fig. 5 shows the joint actual bids of the winning general contractor and the general contractor’s winning subcontractor, and the joint true costs of the 15 projects in Category 1 as an example.

Based on past literature, this result is consistent with the four experiments conducted by Dyer et al. (1989) in which both inexperienced students and experienced executives suffered the winner’s curse in three of the four experiments, and the profit just exceeded zero in the other experiment.

In the multistage bidding game, the results indicated that the winning subcontractors, in their part of the project, suffered the winner’s curse in 77 out of the 90 projects, representing approximately 86% of the projects. Additionally, in the other experiment, the winning subcontractors in their part of the project, suffered the winner’s curse in 77 out of the 90 projects, representing approximately 86% of the projects.

Therefore, due to the multistage bidding environment, adverse selection and the winner’s curse problem is compounded in most of

Table 2. Comparison between MSG and SSG from the Winner’s Curse Perspective

<table>
<thead>
<tr>
<th>Case</th>
<th>Percentage of projects that give positive profits</th>
<th>Percentage of projects that give less losses than the other case</th>
<th>Average percentage of losses relative to the overall project true cost</th>
<th>Average percentage of losses relative to the GC part of the project</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSG</td>
<td>16.66</td>
<td>62.22</td>
<td>1.20</td>
<td>1.19</td>
</tr>
<tr>
<td>MSG</td>
<td>5.56</td>
<td>37.78</td>
<td>1.38</td>
<td>1.21</td>
</tr>
</tbody>
</table>
the projects in the MSG. This being the case, the project that incorporates a multibidding environment is expected, due to suffering more losses than those of a single-stage bidding environment, to face more conflicts, claims, and disputes for all the associated stakeholders.

From the general contractor perspective, the results indicated that the winning general contractors suffered, on average, approximately the same percentage of losses relative to the true cost of their part of the project, as shown in Table 2. Therefore, the general contractors have no preference for either MSG or SSG from the winner’s curse perspective. They might prefer the SSG over the MSG due to the aforementioned increased amount of conflicts, claims, and disputes associated with the MSG. On the other hand, they might prefer the MSG over the SSG based on the size of the project. Fig. 6 shows the comparison between the overall actual profit or losses of the MSG and those of the SSG for each project in Category 1 as an example. Moreover, the X-axis (0 on the Y-axis) in the Fig. 6 represents the joint true cost of the projects in Category 1.

Using SRNNE Optimal Bid Function for Both SSG and MSG as compared to the Random Bid Choice Model

The SRNNE optimal bid function provides contractors with a tool to avoid falling prey to the winner’s curse. Moreover, the SRNNE is derived to be used for symmetric bidders within the same stage of bidding. Thus, it is assumed that the SRNNE is used separately at each stage of bidding for the MSG. Based on the results of both SSG and MSG, it was found that using the SRNNE optimal bid function resulted in positive profits in 100% of the projects. In other words, all optimal bids are greater than the true cost of the projects. Using the SRNNE optimal bid function does not guarantee that the contractor will win the bid, but it guarantees that the contractor will not suffer, on average, from the winner’s curse in case of winning the project contract.

Furthermore, the optimal bids give a strategic profit only to be above the project true cost. Based on the implemented model’s results, the average of the overall earned profits is 1.31 and 1.27% relative the joint project true cost for SSG and MSG, respectively. Fig. 7 shows the comparison between the joint actual winning bids’ profits or losses and the earned joint optimal profits for the 15 projects in Category 1 for both SSG and MSG. The X-axis (0 on the Y-axis) in Fig. 7 represents the joint true cost of the project.

Experience-Based Bidding Model

The learning module was introduced to the random bidding model in order to examine the effect of learning from past experience and bid decisions on the results of the SSG and MSG. The learning module is following the previously described Roth-Erev reactive reinforced learning with an assumed value of (0.2) for each of the forgetting $\theta$ and experimenting $\alpha$ parameters. In general, based on the authors’ point of view, a learning model is more representative of the construction bidding in reality. Because contractors gain more bidding experience with time, they learn how to prepare bids to mitigate the likelihood of the winner’s curse and increase the probability of their long-term survivability. Therefore, learning and benefiting from information gained from every bidding competition are important factors of real construction competitive bidding. This being the case, the experience-based bidding model was implemented to compare its results with those of the
random bidding model and analyze the effect of learning on contractors’ bid decisions.

From the simulations of the experience-based bidding model, it is demonstrated that the MSG results in less overall losses than the SSG, which is opposite what happened in Model 1. As shown in Table 3, in the experience-based bidding model the MSG resulted in less overall losses and more positive profits in 68 projects out of the 90 projects, representing approximately 75.56% of all the projects bidding for in the six project categories. By comparing this result to that of the random bidding model, which was only 37.78%, it is obvious that the learning from gained bidding experience aids contractors in the MSG to mitigate the winner’s curse more than those in the SSG.

The aforementioned result of the experience-based bidding model is considered reasonable in the MSG; there is more chance for learning in the same round (same project contract competition) than in the SSG. In the MSG, it is expected that learning is going to happen twice, once by the subcontractors and the other by the general contractors. Therefore, as shown in Table 3, the MSG started to give better results than the SSG from the perspective of suffering from the winner’s curse problem when the learning behavior was introduced to the model. Fig. 8 shows the comparison between the overall actual profit or losses of the MSG and those of the SSG of the learning model for each project in Category 1 as an example. Moreover, the X-axis (0 on the Y-axis) in Fig. 8 represents the joint true cost of the projects in Category 1.

**Fig. 8.** Category 1 of the learning model: overall MSG versus SSG actual profit or losses

<table>
<thead>
<tr>
<th>Model</th>
<th>Percentage of the projects that give less losses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random bidding model</td>
<td></td>
</tr>
<tr>
<td>SSG</td>
<td>62.22</td>
</tr>
<tr>
<td>MSG</td>
<td>37.78</td>
</tr>
<tr>
<td>Learning model</td>
<td></td>
</tr>
<tr>
<td>SSG</td>
<td>24.44</td>
</tr>
<tr>
<td>MSG</td>
<td>75.56</td>
</tr>
</tbody>
</table>

**Conclusion and Future Work**

The winner’s curse is a major concern associated with construction bidding. In fact, contractors suffer from the winner’s curse for a variety of reasons including inaccurate estimates of project cost; new contractors entering the construction market; minimizing losses in case of recession of the construction industry; strong competition within the construction market; differential opportunity costs, which can affect the behavior of contractors; and the intention to win the project and remedy the losses through change orders, claims, and other mechanisms.

Through this paper, the authors identified and compared the degree of the winner’s curse in two common construction bidding settings: single-stage bidding and multistage bidding. Furthermore, the authors analyzed the effect of the learning mechanism on the results of the construction bidding process. To this end, the results of both the random and experience-based bidding models demonstrated that in construction bidding the majority of the winning subcontractors as well as general contractors suffer from the winner’s curse in both single-stage and multistage bidding environments. However, the winner’s curse is more severe in the multistage bidding environment. On the other hand, when learning is introduced, it was shown that the multistage bidding environment results in less instances of the winner’s curse than the single-stage bidding environment. This result may be because there is more opportunity for learning in a multistage bidding environment than in a single-stage bidding environment. In this paper, it has also been demonstrated that the SRNNE optimal bidding methodology in both single-stage and multistage bidding environments provides contractors with a tool that might enable them to refine their decisions in a further dimension and increase the probability of earning positive profits. Furthermore, it is anticipated that this research would provide contractors with guidelines to mitigate the effect of the winner’s curse in the construction industry, and consequently have a positive impact on the associated contracting parties, projects, and overall construction industry. There are several opportunities for further research related to the work conducted in this paper.

First, there are a lot of disturbing factors that affect the bidding decision in reality such as strategic issues, fear, and instinct. Such disturbing factors can highly affect the results of the bidding situation. Therefore, the authors recommend further development of a simulation model considering those factors and compare the results with those of the model of this research. It is anticipated that the results of this suggested comparison will be beneficial for the profession to better understand the bidding decision-making processes.

Second, the aforementioned SRNNE optimal bid function considers only a strategic amount of profit to avoid the winner’s curse. Therefore, the authors recommend the extension of the SRNNE optimal bid function to include more factors associated with bid preparation such as markup, overhead costs, and contingency costs. In addition, future theoretical work should consider making the general contractors’ and subcontractors’ bids in the application of the SRNNE optimal bid function interrelated rather than independent as assumed in this research.

Third, based on the assumptions of the experience-based bidding model, the contractors continue learning from one project to another within the 15 projects in the same category, and then start over from the beginning at the next category. Thus, for further research, it is recommended to study the effect of learning on the results by modeling more projects within the same category and examine if learning can lead to bids that fully avoid the winner’s curse problem or not.
Fourth, it is believed that cooperative game theory can be applied to analyze construction bidding when an integrated project delivery system is applied. This paper applied the noncooperative game theory concept to analyze construction bidding and its correlation with the winner’s curse. To this end, cooperative game theory—the second type of game theory—is used to study the interactions among coalitions of players. From a game theory perspective, a coalition is simply a subset of the set of players that coordinates strategies and agrees on how to divide the total earned payoff. One the other hand, integrated project delivery (IPD) is an approach that combines people, systems, industry structures, and practices into a process that effectively utilizes the talents and abilities of all associated parties to meet the desired project results and maximize efficiency. Such application of cooperative game theory concept in construction bidding exercising the IPD principles shall help all associated parties to simultaneously achieve their objectives.

References