An Evolutionary Game Study of the Behavioral Management of Bid Evaluations in Reserve Auctions

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ABSTRACT Winner determination in current auctions is often performed separately by two groups: the technical expert group and the business expert group. In general, there is a strong negative correlation between technical and business attributes, and it will cause antagonistic feelings and noncooperative behaviors between the two groups under the premise of bounded rationality. First, this paper constructs a game model between the management department and experts and analyzes the conditions for achieving stable equilibrium solutions. Then, we analyze the evolutionary paths and the influencing factors of relevant behaviors based on evolutionary game theory, which reveals the influence from the individual to groups. Finally, to systematically and quantitatively study bid evaluation behaviors, a simulation system based on MATLAB GUI shows the influences on the evolutionary results as the initial conditions and decision parameters change. The study makes positive contributions to the management of bidding evaluations to improve the fairness of the bid evaluation mechanism.

INDEX TERMS Grouped bid evaluation, evolutionary game theory, behavioral analysis, numerical simulation.

I. INTRODUCTION

Auctions are a basic mechanism for trading that are widely used in contemporary economies. Currently, with advances in network techniques, online reverse auctions are regarded as popular and efficient channels to purchase goods by large businesses and administrations. As early as 2007, as estimated by Hewlett-Packard, the $2.7 billion auction contractors authorized by Sun Microsystems had accounted for 70% of the company. Motorola, IBM and Dell are representative users of this auction method [1]. The bid evaluation process is a key part in reserve auctions, and the winner determination results will directly affect the quality of centralized procurement for large enterprises and administrations. Therefore, bid evaluation is an important area of research in e-commerce. Since the products purchased often have more than one attribute (e.g., price, quality and delivery time), price is not the only criterion to consider. Therefore, the method of choosing the winner is a multiattribute decision-making process.

In practice, a winning bid is selected through a specific bid evaluation procedure. When there is a procurement requirement, the e-procurement department makes a public tender announcement on the Internet. Then, suppliers who find this information will submit sealed bids and wait for the initial screening. All qualified bids are posted on the website. The next stage is the bid evaluation process.

Bid evaluation for large construction projects and equipment is highly professional. The winner is determined based on the attribute scores, which are marked by a qualified group of referee experts [2]. People with certain qualifications are called bid evaluation experts. In the actual bid evaluation process, we usually divide attributes into technical attributes (e.g., performance, safety) and business attributes (e.g., price,
service). Similarly, the experts are divided into two groups: technical experts and business experts. Technical experts usually come from technical and production departments, and business experts usually come from business department. No communication between the two groups is allowed during this process. The weighted sum of all experts on the corresponding attributes is the total score of the bid. The bid with the highest score will be the winner. This novel auction is called a grouped multiattribute auction (GMAA) [3]. Online bidding process of a GMAA in large enterprises and government departments is described in Fig. 1.

FIGURE 1. Online bidding process of GMAA.

In general, technical and business attributes have a negative relationship. For the former, the higher they are, the better. For the latter, the lower they are, the better. For example, it is easy to know that high-quality products are usually not cheap. Moreover, the two groups of experts have different preferences and will be more concerned with their own interests. Cooperation will not last forever. Therefore, a GMAA has the following features:

1) There is a strong negative correlation between business and technical attributes.
2) Technical experts and business experts are usually non-cooperative, and they shoulder different responsibilities for their companies.
3) The differences in bid evaluation between the two groups will deepen their antagonism toward each other.

As a result of the participation of experts and the characteristics of attributes, the bid evaluation results will be complex. Moreover, bid evaluation experts and management departments have multiple participants in each process. We take them as two groups. Because of the complex bid evaluation environment, they might work several times in the short term and be unable to obtain all information about the bid. Furthermore, the participants do not know others’ strategies in each bid evaluation process. They will consider personal preferences more in decision-making.

By studying the actual evaluation data of enterprises, our team concludes that antagonism exists and increases over time in the bid evaluation process and that it will inevitably affect the fairness of bid evaluation results [4]. Therefore, the question of how to manage bid evaluation experts effectively to optimize the behaviors of bid evaluation experts and improve the fairness of bid evaluations is a very meaningful research topic. Considering the bounded rationality of bid evaluation experts and management departments, we will study the behaviors of experts and management departments based on evolutionary game theory (EGT). The behavioral evolution of the two groups can provide guidance for bid evaluation and management. The overall flow chart of research idea and method is shown in Fig. 2.

FIGURE 2. Flow chart of research idea and method.

Since referee experts and management departments have different abilities of learning and imitating, they usually make decisions under diverse conditions. In fact, based on the premise of bounded rationality, decision-making is an evolutionary game process for bid evaluation experts and administrative departments. To improve the fairness of the bid evaluation process and to enhance the management level, based on evolutionary game theory, we make the following contributions:

1) We establish an evolutionary game model and theoretically study the existence conditions and evolution rules of evolutionary stable strategies (ESSs), which contributes to analyzing the behaviors of referee experts
and management departments in the bid evaluation process.

2) The simulation system is developed based on MATLAB GUI, and it quantitatively shows the impact of changing the initial conditions and decision parameters on the evolutionary results.

3) The conclusion provides specific measures to promote the cooperation of experts and the supervision of management departments.

4) The method in this paper can provide a theoretical basis for similar multiattribute group decision-making problems.

The remainder of this paper is organized as follows: Section II provides a literature review of the related topic. Section III introduces the basic contents of EGT and its application fields. Section IV proposes the research hypotheses and builds the evolutionary game model; then, the equilibrium behavioral analysis of referee experts and management departments is conducted in Section V. Section VI discusses the simulation system with several specific examples. Section VII discusses the simulation results. Conclusions are drawn in Section VIII.

II. LITERATURE REVIEW

Multiattribute reserve auctions have attracted much interest in recent years [5]. Perrone et al. [6] reviewed the progress of multiattribute auctions and analyzed auctions with two attributes (price and time). Some scholars found the uncertainty of long-term supply behaviors using the state space model. Numerical simulation showed that the proposed plan would obtain better utility. Papakonstantinou and Bogetoft [7] proposed a new multidimensional auction to better estimate uncertain quality and cost. Kersten et al. [8] established a concession model in multiattribute auctions and applied it in real experiences. The results showed that this model could enhance the transparency of the auction mechanism. Moreover, there were some applications of multiattribute reserve auctions in other fields. Cheng et al. [9] proposed a multi-attribute double auction for perishable supply chain transactions. Pla et al. [10] classified attributes into three categories: verifiable attributes, unverifiable attributes and the attributes given by the auctioneer. Then, a novel Vickrey-based reserve auction with multiple attributes was proposed based on the classification above, and it was successfully applied in supply chain management. Combined with Chinese practice, He et al. [11] proposed a multiattribute reserve auction for public construction plans. Zhang et al. [12] initially proposed a multiattribute auction that was applied in transportation purchasing. The auction mechanism could efficiently reduce the shipper’s cost. Based on the method of approximation algorithm, a multiattribute reverse auction mechanism was presented for resource purchasing in cloud computing [13]. Shi et al. [14] introduced a privacy-preserving degree-matching multiattribute auction mechanism for a power grid system field. During the International Conference on Tools with Artificial Intelligence, Shil and Sadaoui [15] proposed multiattribute and unit combinatorial reverse auctions and gave the solutions that could effectively solve problems in winner determination.

One of the most important procedures in a GMAA is winner bid determination. The question of how to determine the optimal bid is an essential process to consider. Scholars have performed many practical studies on winner determination problems. Ray et al. [16] developed a Markov decision-making process (MDP) to analyze winner determination in multiattribute auctions for the selection of good-performance products. To enhance utilities and bid efficiency, Carbonneau and Vahidov [17] introduced a concession-making model to multiattribute auctions in a single-attribute market environment. The results were also proven by the simulation of real data from eBay. Rao et al. [18] shifted attention from traditional indivisible goods to divisible goods, and a decision-making mechanism with a minimum bid increment method was introduced. The mechanism could enhance the authenticity of the attribute information given by the bidder. Gao et al. [19] set up a novel winning bid determination process based on the idea of TOPSIS that contained three attribute categories (business attributes, technical attributes and price). A novel multiattribute reverse auction containing a bilevel distributed decision-making model was constructed [20]. To discuss the influence of attributes on the bid evaluation process, we designed a simulation system to demonstrate the bid evaluation behaviors that influenced winner bid decision-making in a GMAA with business and technical attributes based on the multiagent method [3]. The simulation results indicated that behaviors such as raising bid scores and pressing bid scores would increase over time. Then, we provided a modified bid evaluation procedure to improve fairness. Clearly, scholars have made great efforts on mechanism design to solve the winner determination problem. However, the impact of human behaviors on the problem has not been given enough attention.

In academic research, behavioral analysis related to auctions has attracted the attention of scholars. In the early period, Saidi and Marsden [21] found that the number of bidders was related to bidding interests more than the number of bids, which was significant for enhancing the accuracy of bidding result prediction. Rodriguez et al. [22] discovered that evaluation fatigue was probably a noticeable factor affecting the peer review process, and the conclusion they made was based on a classification study of experts’ behaviors in conference bidding from an international library digital joint conference in 2005. Burguet and Perry [23] compared the equilibrium bidding function of honest bidders and bribers and then discussed the effects of bribery that cause inefficient outcomes within auction activity. This improper behavior would greatly affect the fairness of auctions. Peters and Bodkin [24] found four key issues that would lead to improper behaviors between bidders and tenderers in auction activity. To decrease the probability of bribery, Chang and Chang [25] proposed a method to determine fraudulent behavior in online
auctions and proposed a novel concept named behavior status identification. This research gave support to stakeholders regarding fraud detection. A laboratory experiment to study bidder behaviors in multiattribute auctions was performed with three different conditions [26]. Podwol and Schneider [27] analyzed the changes in bidder behavior from standard to nonstandard during the auction process and found that people in auctions do not follow standard behavior. In a sealed-bid environment, Kamiji [28] analyzed different kinds of bidding behaviors between online search engines and business advertisers, and he then performed a simulation to illustrate that interests could be gained if they changed bidding strategies. He et al. [11] analyzed the chosen strategy of the bidder and tenderer within the bid procedure under the assumption that the tenderer’s preference was open. They found that the bidder would place more attention on bidding strategy improvement rather than corruption behavior if there was more transparency within procurement.

EGT is a powerful tool for solving problems in behavioral operation management (BOM) and other fields, especially economics. Li et al. [29] proposed a novel method to calculate the ESS of players who had no incentive to change their strategy based on the level-k equilibrium concept. From the individual perspective, Chatterjee et al. [30] theoretically advanced a step, linking EGT and learning theory in research on the behavioral evolution of individuals. A two-phenotype duplicate binary matrix replication dynamics model was built in view of people’s own purpose [31]. The model analyzed the changes in individuals’ behavior in communication based on the EGT concept. Stai et al. [32] studied the evolutionary dynamics of user strategy selection in a network based on graphical EGT and analyzed the ESS of the system with changes in preference over time. Shi et al. [33] focused on the supplier relationship in a large construction project. An evolutionary game model was established to analyze the cooperative behaviors of multiple suppliers. From the economic perspective, Wang et al. [34] investigated the evolution of bidding strategies and behaviors of a generation company in an electricity market with flexible price demand by means of an incomplete information evolutionary game. The outcomes showed that dynamic changes in behaviors would happen with adaptive learning. Li et al. [35] discussed the behaviors of retailers in collecting information under competitive conditions and the impact related to information leakage using EGT. Because companies usually do not tend to shift as a reaction to payoff differences at once, Dijkstra and Vries [36] employed an evolutionary framework to study the magnitude of changes in behaviors over time. In other related fields, EGT was used in the selection of an optimal defense strategy in a dynamic network [37]. Su et al. [38] analyzed the equilibrium strategies of producers and consumers in agricultural product sales using EGT. The results indicated that we should take business motivation and the environment as a major concern. Using the biological paradigm of evolutionary games, Chen [39] set up an ecological industry chain with an evolutionary game model that had three phases. Moreover, EGT was used in a behavioral study of electronic seal usage supervision [40]. In short, EGT has become an important theoretical tool for studying behavioral operation management, economics and management science.

Clearly, recent behavioral studies on multiattribute auctions have mostly focused on bidders and tenderers, and less attention has been paid to the regulatory behavior and evolution occurring in the bid evaluation process. By studying the actual evaluation data of enterprises, our team has concluded that antagonism exists and will increase over time in the bid evaluation process [4]. We established a modified bid evaluation process through role-playing experience to reduce the antagonism in referee experts and performed some research showing that the antagonism existing in a GMAA can be alleviated by optimizing the bid evaluation mechanism with a multiagent model [3]. The results show that individual behavior has an important influence on group decision-making. It is a nonnegligible factor for any system with people involved when the traditional assumption of perfect rationality is abandoned.

In previous studies, we found the existence of antagonism and tried to eliminate it by improving the bid evaluation mechanism [3], [4]. However, there are many factors from the internal and external environments that affect participants’ behaviors. The antagonism will be more serious over time. To further explore the behaviors of bid evaluation participants and to enhance bid evaluation fairness, considering the bounded rationality, we make great efforts to quantify the factors and determine the equilibrium of behavioral evolution using evolutionary game theory. This study contributes to predicting the strategy selections of experts and departments after several bid evaluation participations. Moreover, we take experts and management departments as two game subjects. This study on the evolutionary path of bid evaluation behaviors under supervision will be an interesting and meaningful topic.

III. EVOLUTIONARY GAME THEORY

Evolutionary game theory is based on bounded rationality and takes groups as research objects. It believes that the decision made by an individual is realized based on the dynamic process of imitation, learning and mutation. According to the concept of biological evolutionary replication dynamics, a player who has a low interest strategy will transfer (imitate) to a higher interest strategy. The proportion of members with different strategies in groups will change and finally reach an evolutionary stable state [41], [42]. The rate of change in the proportion of a specific strategy and its weight are directly proportional to the profit over average benefits.

Replication dynamics and evolutionary stable strategy (ESS) are important concepts in evolutionary game theory. If a strategic space is $S$, the proportion of individuals who choose strategy $i$ is $x_i$, $\sum_{i \in S} x_i = 1$. Let $F(x_i) = \hat{x}_i$; the replicator dynamics equation is

$$\dot{x}_i = (f_i - \bar{f}),$$

(1)
where $f_i$ is the interest of strategy $i$, and $\bar{f}$ is the average interest of all individuals. The point at $F(x_i) = 0$ is an evolutionary stable point. The evolutionary stable point at $F'(x_i) < 0$ is an ESS.

The methodology of this study is as follows. In the process of bid evaluation, there are two main participants: experts and management departments. Since the hypothesis of rational man is not suitable to complex conditions that contains various factors as individual preference, information asymmetry, etc., under the premise of bounded rationality, the participants’ strategy selection will be a dynamic evolutionary process. This paper uses EGT, which is the first application to study the behavioral evolution rules of bid evaluation participants and find an equilibrium state. We define the factors that have an impact on participants’ behaviors and establish a two-party evolutionary game model. The replication dynamics concept is used to find the existence conditions of equilibrium behavior. In addition, Numerical experience overcome the shortcomings of traditional role experiment with high expense and low efficiency. The simulation system based on MATLAB demonstrates the feasibility of the model and can operate without too much time; in particular, the factors that have an impact on participants’ behaviors are analyzed. This research contributes to analyzing and predicting the behavioral evolution of bid evaluation experts and management departments to propose timely management strategies to make the behavior of experts evolve in the desired direction. Furthermore, it provides a theoretical basis and decision-making guidance for bid evaluation management.

### IV. PROBLEM DESCRIPTION AND MODEL BUILDING

For the purpose of maximizing personal profits, it is highly possible that in the process of grouped bid evaluation, experts are usually opportunistic. This condition will be increased if a negative correlation exists between the two groups. When experts have strong noncooperative feelings and behaviors, they have two strategies: cooperation and noncooperation. Noncooperation means that the experts just seek maximum profit and deliberately pursue the result in which the object with their best attributes wins each time. Specific performance is achieved by lifting and pressing bid scores. Cooperation means that experts maintain their objectivity and consider their behaviors from the perspective of the whole company. Bid evaluation management departments also have two strategies: supervision and nonsupervision. When they choose the former, supervision will require the necessary human, material and financial resources. Therefore, this strategy might incur fees in supervision, including fees that are even higher under certain circumstances. The cost can be compensated by increasing the departments’ investment in fairness and in incentives for purchasers and suppliers during the bid evaluation. Since there are many technical and business experts in grouped multiattribute auctions, maintaining fairness in the bid evaluation process is a key issue in the management department. Thus, we pose the following three questions.

#### How can departments make a decision when the categories of experts are unknown? How can experts and departments reach a win-win situation and maintain a harmonious bid evaluation atmosphere? What kind of influence will affect fairness if experts are noncooperative and departments do not supervise?

To solve these problems, we construct a payoff matrix between referee experts and management departments. The research hypotheses and related symbols are defined as follows.

**Research hypotheses:**

**Hypothesis 1:** The attributes of the purchase are divided into technical and business attributes. The technical attributes include performance, configuration and safety. The business attributes include price, warranty and after-sales service. There is an inherent negative correlation between the two categories.

**Hypothesis 2:** Bid evaluation management departments are characterized by bounded rationality and have no knowledge of the decision types and characteristics of each referee in the expert database.

**Hypothesis 3:** The experts have the abilities of learning, imitation and communication, and they are not completely independent of bounded rationality. In general, experts can be viewed as a large group with a certain weight; meanwhile, management departments are also viewed as a group.

Definitions of related parameter are shown in Table 1.

| Symbol | Description |
|--------|-------------|
| $a$    | The income of an expert who selects a cooperation strategy |
| $d$    | The income of an expert who selects a noncooperation strategy |
| $b$    | The basic income of a management department |
| $e$    | The penalty of a management department without supervision |
| $p$    | The penalty of an expert whose noncooperative behaviors are found under supervision |
| $c_1$  | The cost of a management department when performing supervision |
| $c_2$  | The bid loss cost of a management department without supervision when experts are noncooperative |
| $c_3$  | The expense of changing or adding new experts when their noncooperative behaviors are supervised |
| $r$    | The reward from buyers and suppliers (tenders) to departments if they find noncooperative behaviors |
| $r_0$  | The reward from buyers and suppliers (tenders) to departments if they find cooperative behaviors |

The approaches of supervision include psychological assessment and the analysis of experts’ behaviors in a previous bid evaluation process through data mining. The aim...
TABLE 2. Payoff matrix for a referee expert and management department.

| Strategy          | Management department (A) |
|------------------|---------------------------|
|                  | N                        | S                        |
| Referee expert   | $u_{11}^E$ | $u_{12}^E$ | $u_{11}^E$ | $u_{12}^E$ |
| (E)              | $u_{21}^E$ | $u_{22}^E$ | $u_{21}^E$ | $u_{22}^E$ |

of experts who select a noncooperative strategy is to let the preferred bid ultimately win; thus, we have $d - a > 0$.

The payoff matrix for a referee expert and management department is described in Table 2.

For referee expert, strategy C and N stand for cooperation and noncooperation, respectively; for management department, strategy S and N stand for supervision and nonsupervision, respectively. $u_{11}^E = u_{12}^E = a$, $u_{11}^N = b - e$, $u_{12}^N = b + r_0 - c_1$, $u_{21}^E = d$, $u_{22}^E = b - c_2 - e$, $u_{21}^N = d - p$, and $u_{22}^N = b + r_1 - c_3$.

V. EQUILIBRIUM BEHAVIORAL ANALYSIS

A. PURE STRATEGY EQUILIBRIUM ANALYSIS

For the game model in Section IV, since $d - a > 0$, $u_{21}^E > u_{11}^E$.

If

$$\begin{align*}
    p < d - a \\
    r + c_2 + e - c_3 < c_1
\end{align*}$$

the pure strategy Nash equilibrium solution is (N, N).

If

$$\begin{align*}
    p > d - a \\
    r + c_2 + e - c_3 > c_1
\end{align*}$$

the pure strategy Nash equilibrium solution is (N, S).

If

$$\begin{align*}
    p > d - a \\
    c_1 < \min\{r_0 + e, r + c_2 + e - c_3\}
\end{align*}$$

the pure strategy Nash equilibrium solution is (C, S).

If

$$\begin{align*}
    p > d - a \\
    r + c_2 + e - c_3 < c_1 < r_0 + e \\
    p > d - a \\
    r_0 + e < c_1 < r + c_2 + e - c_3
\end{align*}$$

there is no pure strategy Nash equilibrium solution.

For the four equilibrium strategies, we obviously expect (C, N) to be the best strategy; in this situation, the referee experts will select a cooperation strategy, and the management department will carry out a nonsupervision strategy. We can see from the conclusion that the pure strategy Nash equilibrium (C, N) does not exist. In fact, this is consistent with reality: rational experts cannot select the cooperation strategy when management departments do not enforce supervision in the long term.

However, the strategy (N, S) is the worst result, the referee experts will select a noncooperation strategy even though the management department carries out a supervision strategy. The management departments will give up supervision if the pure strategy Nash equilibrium solution is (N, S) because it will make no difference with respect to the experts’ noncooperation behaviors even though the departments try their best to execute a supervision strategy.

Clearly, the strategy (C, S) will be the best pure equilibrium solution we can derive; in this case, the referee experts will select a cooperation strategy, and the management department will carry out a supervision strategy. For management department, supervising is well worth the effort; otherwise, it will be difficult to form experts’ cooperation behaviors.

It can be seen from the equilibrium conditions above that the more severe the punishment is, the more likely the bid evaluation experts will choose the cooperative strategy; additionally, the higher the cost of supervision is, the lower the enthusiasm of the supervising department for choosing the supervision strategy. That is, the higher the cost of supervision, the less likely the evaluation experts will choose a cooperative strategy.

In fact, the above pure strategy Nash equilibrium states rarely exist in actual bid evaluation practice; more often, the state is characterized by the transformation of and evolution between the different pure Nash equilibrium strategies. This shows that there is a strong dependency on strategy choices between experts and management departments. Therefore, we will study the evolutionary stable strategies in Section V. B.

B. EVOLUTIONARY STABLE STRATEGY ANALYSIS

If the parameters do not meet the above conditions in Section V. A, that is, there is no pure strategy equilibrium solution, then from the perspective of bounded rationality and multistage decision, the choice of strategy is a dynamic evolutionary process. Thus, the static game model will be transformed into an evolutionary game model.

Since $u_{21}^E > u_{11}^E$, when

$$\begin{align*}
    p > d - a \\
    r + c_2 + e - c_3 < c_1 < r_0 + e \\
    p > d - a \\
    r_0 + e < c_1 < r + c_2 + e - c_3
\end{align*}$$

the game model has no pure strategy Nash equilibrium solution. According to the revenue relationship under different strategies, we propose the following two cases:

Case 1: $u_{11}^E < u_{12}^E$, $u_{11}^E < u_{22}^E$, $u_{11}^E < u_{12}^E$, $u_{12}^E < u_{22}^E$.
Case 2: $u_{11}^E < u_{12}^E$, $u_{11}^E < u_{22}^E$, $u_{11}^E > u_{12}^E$, $u_{12}^E < u_{22}^E$.

Regarding the bid evaluation management departments and experts with bounded rationality, the problem is whether the experts will choose a cooperative strategy, and is the probability that the management departments will not supervise. The replication dynamics equation of the bid evaluation
expert is

$$\frac{dx}{dt} = x(u_E^L - u_E^C),$$

where $u_E^L = ya + (1 - y)a$ is the expected revenue of experts with the cooperative strategy, $u_N^E = yd + (1 - y)(d - p)$ is the expected revenue of experts with the noncooperative strategy, and $u_E^F = x(u_E^L + (1 - x)u_N^E)$ is the average expected revenue of all experts.

Therefore,

$$\frac{dx}{dt} = x(1 - x)(a - d + p - yp).$$

Let

$$x(1 - x)(a - d + p - yp) = 0,$$

thus,

$$y_0 = \frac{(a - d + p)}{p},$$

where $0 < y_0 < 1$.

The replication dynamics equation of the bid evaluation management department is

$$\frac{dy}{dt} = y(u_N^E - u_A^C),$$

where $u_N^E = xb + (1 - x)(b - c_2)$ is the expected revenue of bid evaluation management departments with the nonsupervision strategy, $u_A^E = x(b + r_0 - c_1) + (1 - x)(b + r - c_1 - c_3)$ is the expected revenue of bid evaluation management departments with the supervision strategy, and $u_A^A = yu_N^E + (1 - y)u_M^A$ is the average expected revenue of all bid evaluation management departments.

Similarly,

$$\frac{dy}{dt} = y(1 - y)(c_1 + c_3 - c_2 - r - e + (c_2 + r - c_3 - r_0)x),$$

Let

$$c_1 + c_3 - c_2 - r - e + (c_2 + r - c_3 - r_0)x = 0,$$

then

$$x_0 = \frac{c_2 + r + e - c_1 - c_3}{c_2 + r - c_3 - r_0},$$

where $0 < x_0 < 1$.

To expediently describe (7) and (11), $F(x) = \frac{dx}{dt}$ and $G(y) = \frac{dy}{dt}$.

For the experts, if $y = y_0$ and $F(x) \equiv 0$, all $x$ are in stable states; if $y \neq y_0$, $x_1 = 0$ and $x_2 = 1$ are in stable states. For management departments, if $x = x_0$ and $G(y) \equiv 0$, all $y$ are in stable states; if $x \neq x_0$, $y_1 = 0$ and $y_2 = 1$ are in stable states. The ESS of both sides will be discussed later in the two cases.

**Case 1:** For experts, when $y > y_0$, $F'(0) < 0$ and $F'(1) > 0, x_1 = 0$ is the ESS; when $y < y_0$, $F'(0) > 0$ and $F'(1) < 0, x_2 = 1$ is the ESS. For management departments, when $x > x_0$, $G'(0) < 0$ and $G'(1) > 0, y_1 = 0$ is the ESS; when $x < x_0$, $G'(0) > 0$ and $G'(1) < 0, y_2 = 1$ is the ESS.

**Theorem 1:** In the game model above, if the pure strategy Nash equilibrium solution does not exist and the parameters meet the conditions in Case 1, the proportion of cooperative experts and nonsupervising management departments in the initial groups is $(x, y)$. Then, $A(1, 0)$ and $B(0, 1)$ are evolutionary stable sink points and ESSs. However, $O(0, 0)$ and $D(1, 1)$ are unstable starting points, and $C(x_0, y_0)$ is the unstable saddle point.

**Proof:** The matrix trace and determinants of a Jacobi matrix at $P(x_n, y_n)$ are defined as $Tr(J)$ and $Det(J)$, respectively. According to the stability theory of differential equations, if $Det(J)|_{P(x_n, y_n)} > 0$ and $Tr(J)|_{P(x_n, y_n)} < 0$, the equilibrium point $P(x_n, y_n)$ is stable; if $Det(J)|_{P(x_n, y_n)} < 0$ or $Tr(J)|_{P(x_n, y_n)} > 0$, $P(x_n, y_n)$ is unstable.

From (7) and (11), we have (15), as shown at the bottom of the next page.

The related computed results are presented in Table 3. The conclusion is proven through the results of Case 1.

**Case 2:** For experts, when $y > y_0, F'(0) < 0$ and $F'(1) > 0, x_1 = 0$ is the ESS; when $y < y_0, F'(0) > 0$ and $F'(1) < 0, x_2 = 1$ is the ESS. For management departments, when $x > x_0, G'(0) > 0$ and $G'(1) < 0, y_2 = 1$ is the ESS; when $x < x_0, G'(0) < 0$ and $G'(1) > 0, y_1 = 0$ is the ESS.

**Theorem 2:** In the game model above, if the pure strategy Nash equilibrium solution does not exist and the parameters meet the conditions in Case 2, the evolutionary game model has no ESS. The strategic choices of both sides have a strong interdependence.

According to the conclusions of Theorems 1 and 2, the phase diagrams of group types for referee experts and management departments are shown in Fig. 3.

![Phase diagram of group types for referee experts and management departments](image-url)
TABLE 3. The stability analysis results under different cases.

|          | Det(J)  | Tr(J)  | Det(J)  | Tr(J)  | Det(J)  | Tr(J)  | Det(J)  | Tr(J)  |
|----------|---------|--------|---------|--------|---------|--------|---------|--------|
| x=0, y=0 | +       |        | -       |        | +       |        | -       |        |
| x=0, y=1 | unstable | ESS   | ESS    | unstable | saddle point |
| x=1, y=0 | -       | *      | -       | -      | *       | -      | -       | +      |
| x=1, y=1 | -       | unstable | unstable | saddle point |
| x=x0, y=y0 | -       |        | +       |        | -       |        | 0       |        |

Annotation: * indicates that the value’s sign is uncertain

C. ANALYSIS OF FACTORS INVOLVED IN EVOLUTIONARY STABILITY

Based on the equilibrium analysis above, only Case 1 has ESSs, which are $A(1, 0)$ and $B(0, 1)$. $A(1, 0)$ (cooperation, supervision) is the expected stable strategy that will provide protection to excellent providers, and this steady state can improve the fairness of bid evaluation to a large extent. $B(0, 1)$ (opportunism, nonsupervision) is the most undesirable evolutionary stable state. In this state, the experts will finally select the noncooperation strategy, and the management departments will not play the supervisory role that they should be responsible for. This is the state that we do not want to see.

Thus, we will make greater efforts with regard to the influencing factors of the evolutionary states in Case 1. From Theorem 1, we obtain the final evolutionary results in which either all the experts are cooperative and all the management departments execute the supervision strategy or all the experts are noncooperative and all the management departments execute the nonsupervision strategy. The specific phase diagram of behavioral evolution is shown in Fig. 4.

When the initial state of groups is in OCDB, the system will converge toward $A(1, 0)$; that is, all experts are noncooperative, and all management departments execute the nonsupervision strategy. In this state, neither of them will obtain the maximum expected revenue, but neither will change their strategy. The bid evaluation behaviors will become bad. The existence of opportunistic behaviors will cause losses for purchasing departments and tenderers. When this case occurs, the bid evaluation management departments need to play roles of intervention and supervision through macrocontrol.

When the initial state of groups is in OADC, the system will converge toward $A(1, 0)$; that is, all experts are cooperative, and all management departments execute the supervision strategy. Then, both will achieve a win-win situation and obtain the maximum expected revenue. At this time, the bid evaluation behaviors will be in a benign state, and all management departments will not need to perform any intervention. Meanwhile, the more closely the point $C(x_0, y_0)$ draws to $B(0, 1)$, the larger the area of OADC is; therefore, the probability of the system evolving into $A(1, 0)$ will become larger. Thus, the probability of the system evolving into $B(0, 1)$ will become lower. This is the best mode we expect the system to evolve into.

The area of the OADC is

$$S = \frac{1 - x_0 + y_0}{2} + \frac{c_1 - r_0 - e + a - d + p}{2(c_2 + r - c_3 - r_0)} = \frac{a - d + p}{2p}.$$  \hspace{1cm} (16)

The factors that affect the area of OADC are analyzed as follows.

$$\frac{\partial S}{\partial c_1} < 0, \frac{\partial S}{\partial c_2} > 0, \frac{\partial S}{\partial c_3} < 0, \frac{\partial S}{\partial r} > 0, \frac{\partial S}{\partial r_0} > 0, \frac{\partial S}{\partial e} > 0, \frac{\partial S}{\partial p} > 0.$$  \hspace{1cm} (17)

For Case 1, with the increase in $c_2, r, r_0, p, e$, and $\alpha$, $S$ will increase, and the probability of the system evolving into $A(1, 0)$ will increase. With the increase in $c_1, c_3, d$, $S$ will decrease, and the probability of the system evolving into $B(0, 1)$ will increase.

$$J = \begin{vmatrix} (1 - 2x)(a - d + p - yp) & -px(1 - x) \\ y(1 - y)(c_2 + r - c_3 - r_0) & (1 - 2y)(c_1 + c_3 - c_2 - r - e + (c_2 + r - c_3 - r_0)x) \end{vmatrix}. \hspace{1cm} (15)$$
The probability of the system evolving into $A(1, 0)$ becomes larger; that is, the proportion of cooperative experts will increase, and all the experts will select the cooperative strategy in the later stage. According to the analysis and conclusions above, for both the static game and the dynamic evolutionary game, we conclude that with the increase in $c_2$, $r$, $r_0$, $p$, $e$, $a$ or the decrease in $c_1$, $c_3$, $d$, the proportion of cooperative experts and supervising departments can be improved. Meanwhile, the system’s evolution to the stable state $A(1, 0)$ will be promoted.

For Case 2, the evolutionary game model has no ESS. In this case, the strategic choices between bid evaluation experts and management departments have a strong interdependence. This means that uncertainty exists in the strategy evolution between experts and departments. This bid evaluation situation is not the one that we expect because it is difficult to control and change the strategy selection. Therefore, there is no need to discuss in depth the factors involved in the evolution of Case 2.

VI. NUMERICAL SIMULATION

To provide decision support for bid evaluation and to systematically analyze the evolutionary paths of cooperative and supervisory behaviors, we develop a simulation system for behavioral analysis based on MATLAB GUI. Using this system, we can simulate the evolutionary process of strategy selection under different initial groups and parameters for both referee experts and management departments. When the parameters of the actual environment are accurate, we can better predict the evolutionary process of the system, and further, by analyzing the influence of the parameters on the evolution of the system, we can propose targeted optimization strategies and suggestions.

A. THE IMPACTS OF THE PROPORTION IN THE INITIAL GROUP

In the initial group, the proportion of experts choosing the cooperation strategy is $x_0$, and the proportion of management departments selecting the nonsupervision strategy is $y_0$. If $y_0 = 0.8$, $a = 300$, $p = 200$, $e = 40$, $d = 400$, $r = 1000$, $r_0 = 900$, $b = 500$, $c_1 = 800$, $c_2 = 200$, and $c_3 = 500$, then the evolutionary paths of the experts’ behaviors with different proportions of cooperative experts are shown in Fig. 5. When the initial proportion of management departments selecting the supervision strategy is 0.2, we can clearly see the evolutionary process of experts’ behaviors when the initial proportion of cooperative experts is 0.2, 0.4, 0.6, and 0.8. For the group of experts, we find that cooperation behaviors will evolve into the worst state due to weak supervision, even when the initial percentage of the cooperation strategy reaches 0.6. Most of experts will choose a noncooperation strategy. The fairness of the bid evaluation results will be greatly affected, and the quality of the purchased goods will be difficult to guarantee. Therefore, it is necessary to strengthen the supervision and management over the experts in this situation.

In the initial group, when the proportion of management departments selecting the supervision strategy accounts for 0.8, with all other parameters held constant, the impacts from different proportions of cooperative experts on the evolutionary path are depicted in Fig. 6. The evolutionary process of experts’ behaviors can be observed clearly when the initial proportion of cooperative experts is 0.2, 0.4, 0.6, and 0.8, just as in Fig. 5.

Compared with the evolutionary results in Fig. 5, the results are nearly the opposite, and the experts’ strategy will evolve into cooperation for all 4 cases. Although the proportion of cooperative experts in the initial group is only 0.2, the experts’ behaviors will evolve into the best state due to the increase in the proportion of departments selecting the supervision strategy. The results show that the proportion of departments selecting the supervision strategy has a very significant effect on the evolutionary paths of the behaviors of the experts.

Equally, it is feasible to study the impact on the evolutionary results of department behaviors for the different proportions of cooperative experts in the initial group. At the same time, we can obtain the phase diagrams for different situations.
between experts and management departments, as shown in Fig. 7. Through the evolutionary phase diagram, we can see the interaction process of the behaviors between the two groups over time.

**FIGURE 7.** The evolutionary phase diagrams between experts and management departments.

**FIGURE 8.** The influence of the noncooperation penalty on the evolutionary results.

**FIGURE 9.** The influence of the bid loss cost on evolution results.

**FIGURE 10.** The influence of the cooperation detection reward on the evolutionary results.

**B. THE IMPACT OF THE NONCOOPERATION PENALTY, BID LOSS COST AND REWARD PARAMETER**

If \( p = 500 \) and the other parameters are consistent with Fig. 5, the evolutionary results are shown in Fig. 8. Compared with the simulation results above, for experts, the noncooperation proportion will decrease when the noncooperation penalty is increased. This situation can increase the proportion of cooperative experts, and the probability of the behaviors reaching the optimal state is greatly increased. Therefore, for management departments, we should appropriately increase the opportunity penalty, especially when the proportion of cooperative experts in the initial group is not high enough.

The bid loss cost is an important factor for the experts because it directly affects their benefits. If the bid loss cost is increased to 300 and the other parameters are the same as in Fig. 5, the behaviors of the experts will evolve into cooperation, as shown in Fig. 9. Therefore, raising the bid loss cost can effectively guide bid evaluation experts to choose cooperation strategies.

**FIGURE 11.** Evolutionary results with increased supervision reward.

If we reduce the cooperation detection reward \( r_0 \) and keep other parameters consistent with Fig. 6, the system will no longer evolve toward the optimal state but, rather, the opposite direction when the proportion of cooperative experts in the initial group is 0.2, as shown in Fig. 10. Therefore, increasing the experts’ cooperation reward will promote the evolution to cooperation.

If the supervision reward parameter \( r = 1000 \) and the other parameters are consistent with Fig. 5, the evolutionary results are shown in Fig. 11. The system will not evolve to the worst state when \( r \) is increased. It will evolve toward the optimal state.

The simulation results show that when the cooperation motivation of experts in the initial group is relatively low, this can largely guide the behavior of experts to evolve toward cooperation by enhancing the enthusiasm of the regulatory authorities. Therefore, determining the best value of the supervision reward parameter is a challenging problem for third-party regulatory agencies.
C. THE IMPACT OF THE SUPERVISION COST, TRAINING COST AND NONCOOPERATIVE BID EVALUATION INCOME

If \( c_1 = 750 \) and other parameters are consistent with Fig. 5, the evolutionary results are shown in Fig. 12.

The noncooperative behaviors will decrease when the supervision cost \( c_1 \) falls, and this situation contributes to increasing the proportion of cooperative experts. Therefore, the probability of the experts’ behaviors evolving to the optimal state will increase when the evolution has ended. To a certain extent, reducing the supervision cost can enhance the enthusiasm of departments for supervision. It will also encourage experts to select the cooperation strategy.

If we increase the training cost \( c_3 \) and the other parameters are consistent with Fig. 6, the behavioral evolution of experts is obtained in Fig. 13. The simulation results show that increasing the training cost is not conducive to boosting the speed of the evolution to the optimal state.

Compared with Fig. 5, the simulation results when the noncooperative bid evaluation income is 350 are shown in Fig. 14. Reducing the noncooperative bid evaluation income will improve the cooperative behaviors of experts to a large extent.

VII. DISCUSSION

Because of space constraints, this paper shows only some representative evolutionary impact results. In fact, the system that we develop could simulate different evolutionary conditions in any bid evaluation environment, including, of course, parameter sensitivity analysis.

The simulation results indicate that the proportion of supervision has great effect on experts’ behaviors. High supervision can improve cooperation proportion. Experts will evolve to cooperation with the increase of uncooperative penalty, bid loss cost, cooperation detection reward, supervision income and training cost, and with the decrease of supervision cost and noncooperative bid evaluation income. However, all these measurements are effective except from cooperation reward if the initial cooperation proportion of expert is very low.

The initial proportion of cooperation strategy has influence on evolutionary speed of the system. When the initial proportion is high, parameter changes have great impact on evolutionary path; when the initial proportion is low, the disturbance to ESS is relatively small even if parameters change significantly. How to improve the initial proportion of cooperation should be considered.
The probability of noncooperative behaviors will greatly increase if the following conditions are met: the income from noncooperation is larger than that from cooperation, the supervision cost is high, or the punishment is inadequate. To improve the fairness and sustainability of the bid evaluation mechanism, management departments need to impose a sufficient punishment on the noncooperative experts and reduce their expected income sharply. Meanwhile, it is necessary to build an efficient management team to strengthen the ability to detect noncooperative behaviors. Of course, improving the supervision technique and reducing the supervision costs could increase the probability of the evolution to the best stable state $A(1,0)$.

Third-party regulatory agencies should try their best to increase the incentives for the supervising departments. To scientifically analyze the bid evaluation environment and to reasonably guide the behaviors of experts, they should also estimate the system parameters accurately, including the initial group composition and supervision costs. Then, using the system that we develop, we can promote bid evaluation behaviors in the optimal direction by quantitatively studying the behavioral evolution of experts and management departments or reasonably adjusting the controllable parameters and incentive measures.

VIII. CONCLUSION

Considering the antagonistic feelings and noncooperation behaviors between the two expert groups, the optimization and management of expert behavior will be an important means of improving the fairness of bid evaluation in centralized procurement. As a result of the uncertainty of the expert decision process, bid evaluation management will be complex. Based on bounded rationality and EGT, this paper constructs a game model between experts and departments, and we theoretically prove the existence conditions and evolution rules of ESSs. Then, we analyze the evolutionary path of strategy selection and the factors affecting this evolution. To systematically study bid evaluation behaviors, a simulation system for a GMAAA is developed. The simulation results show that there are some significant effects on the behavioral evolution of experts from the proportion of management departments choosing the supervision strategy. Small changes in the proportion in the initial group will lead experts’ behaviors to ultimately converge toward the opposite state. Changes in the noncooperation penalty, incentive reward and supervision cost will promote bid evaluation behaviors to evolve toward the two opposite directions. The experimental conclusions are consistent with the theoretical analysis. The method in this paper not only is beneficial to evaluation management but also can solve other multiattribute group decision-making problems.

We obtain the following strategic recommendations from the study:

1) We can enhance the enthusiasm for supervision by increasing the incentive strength for management departments.

2) We can improve the initiative of experts to select the cooperation strategy by raising the noncooperation penalty, bid loss cost and cooperation strategy income.

3) We can enhance the supervision of management departments by introducing advanced technology and adjusting the supervision and training cost, which will encourage experts to evolve toward long-term cooperation.

4) As the bid evaluation starts, we should obtain the relevant parameters of the game and quantitatively simulate the evolutionary system; then, we can adjust the strategies in a timely manner to ensure the fairness and sustainability of the mechanism.

5) The noncooperation cost, incentive strength, and proportion of cooperative experts and supervising departments in the initial group should be increased as much as possible. The implementation of these strategies will certainly help to improve the fairness of the bid evaluation mechanism.

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