

Research Article

An Immune Evolutionary Algorithm with Punishment Mechanism for Public Procurement Expert Selection

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In the past decade, fairness in public procurement expert selection has attracted research attention. This paper proposes an immune evolutionary algorithm (IEA) with a punishment mechanism for expert selection, in which an ordered weighted aggregation (OWA) operator is applied to adjust the score weights to reduce expert evaluation committee abuse discretion and Grubbs method is employed to test the outliers. The results from a real-life public procurement case demonstrated that the abnormal experts could be effectively suppressed during the selection process and that the proposed method performed better than either the random selection algorithm or IEA, neither of which considers a punishment mechanism. Therefore, the proposed method, which applied the abnormal data detected in the scoring process to the expert selection process with a punishment mechanism, was proven to be effective in solving public procurement problems that may have doubtful or abnormal experts.

1. Introduction

Public procurement is used in the public sector for small items such as office desks and paper and large items or projects such as electricity, telecommunications, airports, railways, and other infrastructure projects. As public procurement contracts make up around 10%–20% of annual GDP in many countries, it is a significant part of a country's economic activities [1, 2].

In recent years, public procurement bid collusion has been found to be an inherent problem [3]. Generally, as bidding evaluation has a direct impact on the results and is a key step in the bidding process [4], choosing the appropriate public procurement experts is vital to ensuring quality. However, in reality, because the expert assessors have different backgrounds and knowledge, they often assign different preference values to each bidder, which affects the choice of the final supplier. In particular, if some experts receive kickbacks from bidders, this can have a serious impact on the bid evaluation results. While it is difficult to determine whether kickbacks are being received, examining the public procurement scoring process could identify

abnormal scoring and reduce or inhibit the probability of abnormal experts affecting the final supplier's selection.

This study aims to bridge the gap between scoring rules weight analyses and public procurement expert selection. To ensure public procurement transparency and fairness, in this paper, we propose an immune evolutionary algorithm (IEA) with a punishment mechanism for expert selection, apply an ordered weighted aggregation (OWA) operator to adjust the weights of the final scores to reduce expert evaluation committee abuse discretion, and employ Grubbs method to test the outliers. The expert selection method applies any detected abnormal scoring process data to the expert selection process and introduces a punishment mechanism to identify the abnormal experts.

The remainder of this paper is organized as follows. Section 2 reviews previous research on e-procurement (electronic-procurement), expert selection, and the scoring rule weights, Section 3 gives the problem statement and details the theoretical programming and associated methodology, Section 4 gives the computational results from three developed algorithms, and Section 5 gives concluding remarks and outlines future research directions.

2. Literature Review

2.1. E-Procurement. Over the past decade, service quality, transparency, efficiency, and effectiveness have been key foci for public sector management [5]. E-procurement is the use of electronic methods in every stage of the purchasing process from identification of requirements through payment and potentially to contract management [6] and is therefore a new procurement system for the direct and indirect purchasing of goods and services [7]. There has been an increased research on e-procurement [8], such as the factors affecting e-procurement suppliers, the technical frameworks, the use of systems theory to predict public procurement results [9], and the relationships between sustainable procurement and e-procurement [10]. Particularly, for enterprises, various factors, such as enterprise size, top management support, perceived indirect benefits, and business partner influence, are positively and significantly associated with the adoption of e-procurement [11–13]. As most products and services can now be purchased through online platforms, e-procurement has become increasingly common in both the manufacturing and service sectors [14, 15]. Public procurement now harnesses e-procurement with the power of new Internet technology platforms to reduce transaction costs, eliminate bid rigging, allow wider choice of suppliers, bring about better quality, improve delivery, reduce paperwork, lower administrative costs, and so on [16]. Meanwhile, the online transactions between the public sector and business partners bring significant gains in government efficiency and user-friendliness [17, 18].

2.2. Expert Selection. However, public procurement is very different from private procurement because of the greater emphasis on rules and predictability [19, 20]. As a public procurer has less discretion to select any other bidder than the one awarded the highest score, the evaluation committee is critical because the quality and knowledge of the experts can significantly affect the final evaluation results [21]. Therefore, the expert extraction process has become the most sensitive step in public procurement. The traditional manual extraction methods have some disadvantages, such as uneven extraction opportunities, more manual intervention, poor confidentiality, and long time. Along with the development of e-procurement, there has been commensurate development in expert selection systems to guarantee accuracy and fairness and eliminate human interference [22]. The most popular expert selection algorithm is random selection (RS) method [23, 24]. The advantage of RS is easy to operate and high efficiency, but there are still many problems when extracting the experts randomly. First, if the professionalism of the experts is poor, there could be omissions or deviations in the bidding process. Second, if the experts are influenced by private interests, they may seek to distort the bid evaluation. Third, the unreasonable design of the expert database as well as the lack of detailed conditions of experts' positions will lead to inconsistencies between the experts who are extracted by

the expert system and those required by the project. Finally, because of the no-fault public procurement attribution principles, the expert punishment may not be equal to the bidding rights as there are no effective restrictions when experts violate the bidding disciplines.

Other expert selection algorithms or methods have been applied to expert selection problems. Yu used Axure RP tool to design expert selection system [25]; intelligent algorithms such as parallel genetic algorithm [21] and TOPSIS method [26] were used for experts' assignment area. In the procurement process, to prevent and punish bid-rigging behavior, some mechanism should be established [27]. For example, Wang proposed reverse auction punishment mechanism [28], and Ray proposed new multiple attribute relations based on supplier evaluation which included a dishonesty punishment mechanism [29]. In conclusion, the above expert selection algorithms were designed to only focus on expert selection; none have been shown to have the capacity to identify or penalize abnormal experts. On the other hand, punishment mechanisms should be taken into account in the process of expert extraction, as experts and public officials have a tendency to be corrupted [30], so the punishment mechanism should be considered in the process of expert extraction.

2.3. Scoring Rule Weights. The scoring rule weights also influence public procurement. As the main public procurement goal is to determine the optimal combination of high quality and low prices, competitive bidding, and low transaction costs, an absence of corruption or favoritism is necessary and generally assumed. As with any procurement process, product or service price and quality vary depending on the supplier; however, the price and quality are also affected by the procurement criteria. As the buyer wants to optimize the quality and minimize the costs, public procurement criteria design is generally complex. Therefore, scoring rules are needed to assign numerical values to the different quality levels or to transform a value measured on one scale (price or quality) into a measure on another scale (price score or quality score) [1]. Several scoring rule weight methods have been developed, such as fuzzy multicriteria decision-making models for construction contractor prequalification [31], multiple amended weight coefficients for supplier evaluations [32], quality-to-price scoring rules [33], scoring weights for auctions [34, 35], fuzzy approach [36], and hybrid multicriteria models based on the IRN for bidder selection [37]. However, as these methods tend to only focus on the methods for setting the appropriate weights for the various evaluation criteria attributes, they do not consider weight settings for the different experts, especially when experts have serious biases towards a bidder. Generally, scoring rules take the average score of all experts or remove the lowest or highest scores. Therefore, if the scoring weights are not reasonable or the bid is dominated by a major technical expert acting on behalf of the bidder [2], these methods could affect the tenderers' rights and lead to unfair competition.

3. Problem Description and Theoretical Foundation

3.1. Problem Description. Now, public procurement expert selection aims to select appropriate experts but does not focus on how to deal with the abnormal experts. Therefore, if abnormal experts are selected to participate in the public procurement bid evaluation, they are free to act as they wish; therefore, if they are covertly representing certain interests or have received a bribe from a particular bidder, the project efficacy could be severely affected. As each expert gives scores based on their own knowledge and expertise, this type of corruption almost always results in lower quality and higher priced products or services. Because expert selection can significantly affect final procurement and bid evaluation fairness, it is imperative to include punishment for abnormal experts in the expert selection process. This paper is to select appropriate public procurement experts based on the matching degree of their experience and professionalism while limiting their discretion.

3.2. Expert Selection Using an Immune Evolutionary Algorithm. The concept of immunity is proposed based on inspiration from biology [38]. The function of the immune system is to protect the living body from any foreign attack such as disease or harmful cells [39]. There are a variety of molecules, cells, and organs throughout the body, which form part of the immune system. The immune system recognizes malfunctioning and disease-causing elements, which are known as antigens. There are two types of antigens: self and nonself. Self-antigens initially belong to our own system and are harmless, whereas nonself-antigens are disease-causing elements. Recognition of an antigen is essential for the immune system to activate and perform the subsequent response. If the immune system encounters a nonself-antigen, it proliferates and differentiates into memory cells [40]. Evolutionary algorithm (EA) [41, 42] is a search algorithm based on biological evolution mechanisms such as natural selection and natural heredity and can effectively deal with the complex problems that are difficult to be solved by traditional optimization algorithms. Based on the study of the existing research above, the IEA is proposed with combining the immune and evolutionary mechanisms based on the theory of immunity in biology to restrain the degenerative phenomena during the evolutionary process. Because the immune algorithm is apt to turn premature hastily, the genetic variation evolution process was added to optimize it.

The IEA [43] is a computational model based on a combination of the properties associated with the biological immune system and engineering that follows the survival of the fittest principles by simulating the biological genetic evolutionary process. Through iteration, IEA is able to simultaneously select the optimal individuals and suppress the abnormal individuals (such as viruses) because of its inherent characteristics, automatic antigen identification, antibody diversity, distributed detection, learning, and memorization. IEA has many characteristics, including automatic identification of antigen, extraction of features, diversification of

antibodies, distributed detection, learning, memory, and self-programming. So it is regarded as a parallel and distributed self-adapted system with great potentiality in intelligent computation application [44]. IEA has also been successfully applied to model identification, troubleshooting, and other fields such as optimization problems [45]. Because of its powerful capability in disposing of information, it is becoming the research issue of intelligent computation.

The goal of public procurement expert selection is to select the most appropriate experts (professional and experienced) and to limit and punish abnormal experts; therefore, as expert selection involves a continual optimization process that also includes a punishment mechanism, the IEA has the necessary properties. In addition, compared with other more evolution algorithms or swarm intelligent algorithms, the IEA algorithm can obtain optimal performance and is relatively stable. For example, particle swarm optimization algorithm convergence rate is quick, but the final convergence result is easily affected by parameter size and initial population. Genetic algorithm has too many parameters and convergence rate slowly or even hard for high-dimensional problems. IEA not only requires simple parameters but also can improve the convergence. Therefore, because of its powerful capacity to dispose of information, IEA is suitable for the public procurement expert selection process.

As IEA is a global optimization algorithm, it records the information from optimal individuals using mutation and replaces the group evolution with the optimal individual evolution. The IEA mechanism is as follows:

Antigen: the pattern expressed in a pathogen.

Antibody: the cell used to identify an antigen.

Affinity: the degree of fitness between the antibodies and antigens.

Memory cell: the antibody that has an affinity greater than the specified threshold.

When using IEA to solve a problem, the antigen, antibody, and affinity, respectively, correspond to the objective function, the optimization solution, and the matching degree between the solution and the objective function. The IEA process is shown in Figure 1.

- (1) Identify antigens. The antigens are the target functions and constraints.
- (2) Produce initial antibodies. Antibodies are generated in the solution space using a random method.
- (3) Calculate affinities. The affinities determine the fitness between the antigens and the antibodies.
- (4) Update memory cell. The affinities are reordered so that the antibody with the highest affinity is put into the memory cell.
- (5) Use genetic variation operators to produce new antibodies. The genetic variation operation is defined as

$$\psi' = \psi + P_m * \exp\left(\frac{1}{f}\right) * N(0, 1), \quad (1)$$

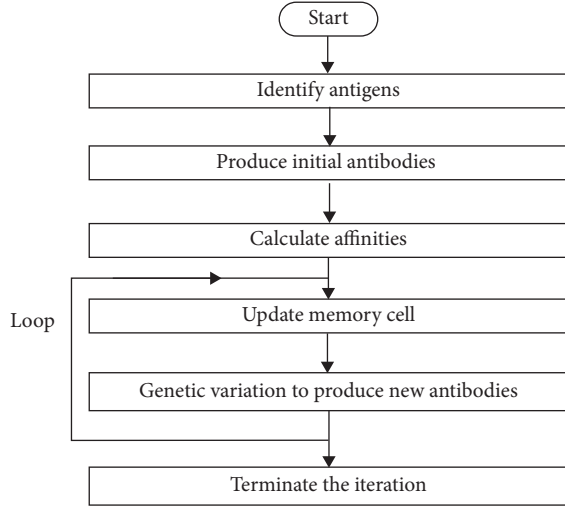


FIGURE 1: IEA flowchart.

where ψ and ψ' are the parent and the child antibodies, $N(0, 1)$ is the Gauss variable with a mean of 0 and a variance of 1, P_m is the mutation probability, and f is the mean value of the affinity from the initial antibody group.

Return to Step (4) and repeat for the next iteration.

- (6) Terminate the iteration. Terminate the generation when the threshold is reached.

3.3. Weight Adjustments Using an OWA Operator Based on Normal Distribution. Traditional scoring rules compute the average score of all experts in the public procurement; for large-scale statistics, the bidding scores generally follow a normal distribution. In the real world, as the collection of n aggregated arguments a_1, a_2, \dots, a_n usually take the form of a collection of n preference values provided by n different individuals, some individuals may assign unduly high or unduly low preference values to their preferred or rejected objects. In these cases, very low weights are assigned to false or biased opinions; that is, the closer a preference value is to the midpreference value, the greater the weight, and the further a preference value is from the midpreference value, the lower the weight. Therefore, to limit the influence of an abnormal expert in the public procurement process, an ordered weighted aggregation (OWA) operator based on a normal distribution can be used to allocate the score weights.

When an OWA operator is introduced to aggregate information [46], the procedure generally has three steps:

- (1) Reorder the input arguments in descending order.
- (2) Determine the weights associated with the OWA operator using a proper method.
- (3) Utilize the OWA weights to aggregate the reordered arguments.

The OWA operator for dimension n is a mapping, $\text{OWA}: R^n \rightarrow R$, that has an associated n vector $w = (w_1, w_2, \dots, w_n)^T$ such that $w_j \in [0, 1]$ and $\sum_{j=1}^n w_j = 1$. Further,

$$\text{OWA}_w(a_1, a_2, \dots, a_n) = \sum_{j=1}^n w_j b_j, \quad (2)$$

where b_j is the j th largest element in the collection of the aggregated objects a_1, a_2, \dots, a_n .

Let x be a continuous random variable, with its probability density function defined as

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2}, \quad -\infty < x < +\infty, \quad (3)$$

where μ and σ ($\sigma > 0$) are constants. Then, x is normally distributed with a mean of μ and a standard deviation of σ .

The normal distribution provides a realistic approximation of the deviation distributions in many experimental situations, especially for the central portion of the deviations. In the following, normal distribution is used to determine the weights for the OWA operator [47].

Let $w = (w_1, w_2, \dots, w_n)^T$ be the weight vector for the OWA operator; then, we define the following:

$$w_i = \frac{1}{\sqrt{2\pi}\sigma_n} e^{-(i-\mu_n)^2/2\sigma_n^2}, \quad i=1, 2, \dots, n, \quad (4)$$

where μ_n is the mean for the collection of $1, 2, \dots, n$ and σ_n ($\sigma_n > 0$) is the standard deviation for the collection $1, 2, \dots, n$, with μ_n and σ_n being obtained using the following formulas:

$$\mu_n = \frac{1}{n} \frac{n(n+1)}{2} = \frac{n+1}{2}, \quad (5)$$

$$\sigma_n = \sqrt{\frac{1}{n} \sum_{i=1}^n (i - \mu_n)^2}. \quad (6)$$

If $w_j \in [0, 1]$ and $\sum_{j=1}^n w_j = 1$, then

$$w_i = \frac{(1/\sqrt{2\pi}\sigma_n) e^{-(i-\mu_n)^2/2\sigma_n^2}}{\sum_{j=1}^n (1/\sqrt{2\pi}\sigma_n) e^{-(j-\mu_n)^2/2\sigma_n^2}} = \frac{e^{-(i-\mu_n)^2/2\sigma_n^2}}{\sum_{j=1}^n e^{-(j-\mu_n)^2/2\sigma_n^2}}. \quad (7)$$

As the mean for the collection $1, 2, \dots, n$ is $((n+1)/2)$, equation (6) can be rewritten as

$$w_i = \frac{e^{-((i-(n+1)/2)^2/2\sigma_n^2)}}{\sum_{j=1}^n e^{-((j-(n+1)/2)^2/2\sigma_n^2)}}. \quad (8)$$

Based on a normal distribution, by assigning lower weights to the false or biased arguments, the OWA operator is able to reduce the influence of any unfair arguments on the decision results.

3.4. Outlier Detection Using Grubbs Method. In statistics, an outlier is an observation point that is distant from the other observations. For normally distributed data, the outlier is a set of measured values that deviate from the mean by twice the standard deviation or more. There are various methods

to detect outliers; in this paper, the Grubbs method is improved and then used to test for outliers.

$$\mu = \frac{x_1 + x_2 + \dots + x_n}{n}, \quad (9)$$

$$s = \sqrt{\frac{\sum_{i=1}^n (x_i - \mu)^2}{n-1}}, \quad (10)$$

$$G_n = \frac{x_i - \mu}{s}, \quad (i = 1, 2, \dots, n), \quad (11)$$

where μ is the mean of the sample, s is the standard deviation of the sample, and G_n is the Grubbs test statistic.

Based on the above algorithm, μ is the average value derived from the OWA operator based on a normal distribution; therefore, we define

$$\mu = \text{OWA}_w(a_1, a_2, \dots, a_n). \quad (12)$$

3.5. Proposed Algorithm. This paper proposes an IEA with a punishment mechanism to select experts for public procurement projects, in which an OWA operator is employed to reasonably adjust the score weights, and Grubbs method is then applied to test for the outliers in the scoring process. The flowchart for the proposed algorithm is shown in Figure 2, the algorithmic steps for which are as follows:

Step 1: Identify the antigens. The objective function is to select the required appropriate experts. The constraint conditions are within the appropriate field and the experts are normal.

Step 2: Produce the initial antibodies. Treat all experts as the initial antibodies, which then constitute the solution space.

Step 3: Calculate the affinities. Define each project as an iteration. The initial affinity is the initial value from each expert; the higher the value, the higher the degree of affinity. At the first iteration, no experts are marked, and the abnormal tag is 0. Additionally, as each expert has some chance of being marked, the affinity can be defined as follows:

$$\text{Fitness (ID)} = V_{\text{initial}} - \sum_{i=1}^n V_{\text{tag}_i}, \quad (13)$$

where V_{initial} refers to the initial value from each expert and the values for V_{tag_i} are defined as follows:

$$V_{\text{tag}_i} = \begin{cases} \neq 0, & \text{tag}_i = 1, \\ = 0, & \text{tag}_i = 0. \end{cases} \quad (14)$$

Step 4: Update the memory cells. Reorder the affinities of all experts in descending order and put the experts with the largest affinities into the memory cells. Output the experts suitable for the bidding evaluation in the memory cells.

Step 5: Calculate the scores using the OWA operator. The selected experts provide individual preferences for

the public procurement project. Reorder these scores in descending order according to the different bidders, and utilize the OWA operator to adjust the weights for the reordered scores.

Step 6: Detect the outliers using Grubbs method. Use the Grubbs method to detect the outliers, mark the abnormal experts, and set $\text{tag}_i = 1$. The outliers refer to some individuals who may assign unduly high or unduly low preference values to their preferred or rejected objects. Input the abnormal experts into the expert selection process; if there are no abnormal experts, the input is empty.

Step 7: Restrain the abnormal experts. Starting from the second iteration, judge the affinity values of each expert. If the values are less than a given threshold, the marked experts are added to a blacklist, after which new experts are added and the memory cells updated.

Step 8: Genetic variation to select new experts. Use the genetic variation operators to select new experts. Return to Step 4 and repeat for the next iteration. To avoid falling into a local optimization, after a certain number of iterations, half of the experts are retained and new experts introduced.

Step 9: Activate the inhibition experts. After some iterations, activate the experts in the blacklist, and reset $\text{tag}_i = 0$; that is, these experts can continue to participate in the bid evaluation. Return to Step 4 and repeat for the next iteration.

Step 10: Terminate the iteration. When no project needs to select experts, terminate the iteration.

4. Case Study and Discussions

4.1. Case Study. This section presents a problem that has 30 experts from a certain furniture field, each of which has at least five years of public procurement experience. The value of experts was initialized based on their specific attributes such as professional titles. The foundation scores for all experts were higher than 80. The initial values for the 30 experts are shown in Table 1, and the distribution of the data is shown in Figure 3. Each project was then defined as an iteration under the assumption that the bid evaluation experts for the subsequent project would be selected after the bid evaluation for the first project. The number of expert committee members shall be odd number at 5.

We implemented the proposed algorithm with Java language in the Eclipse programming environment. Mutation probability $P_m = 0.5$. We extracted experts for 5 projects, so the iteration is 5. The experts for the five projects were selected in turn as selecting bidding evaluation experts for multiple projects at the same time was out of the scope of this paper. The following three algorithms were also used for comparison purposes: RS, IEA, and the proposed algorithm, with the results for the RS and IEA being as shown in Tables 2 and 3. The steps for the proposed algorithm were as follows.

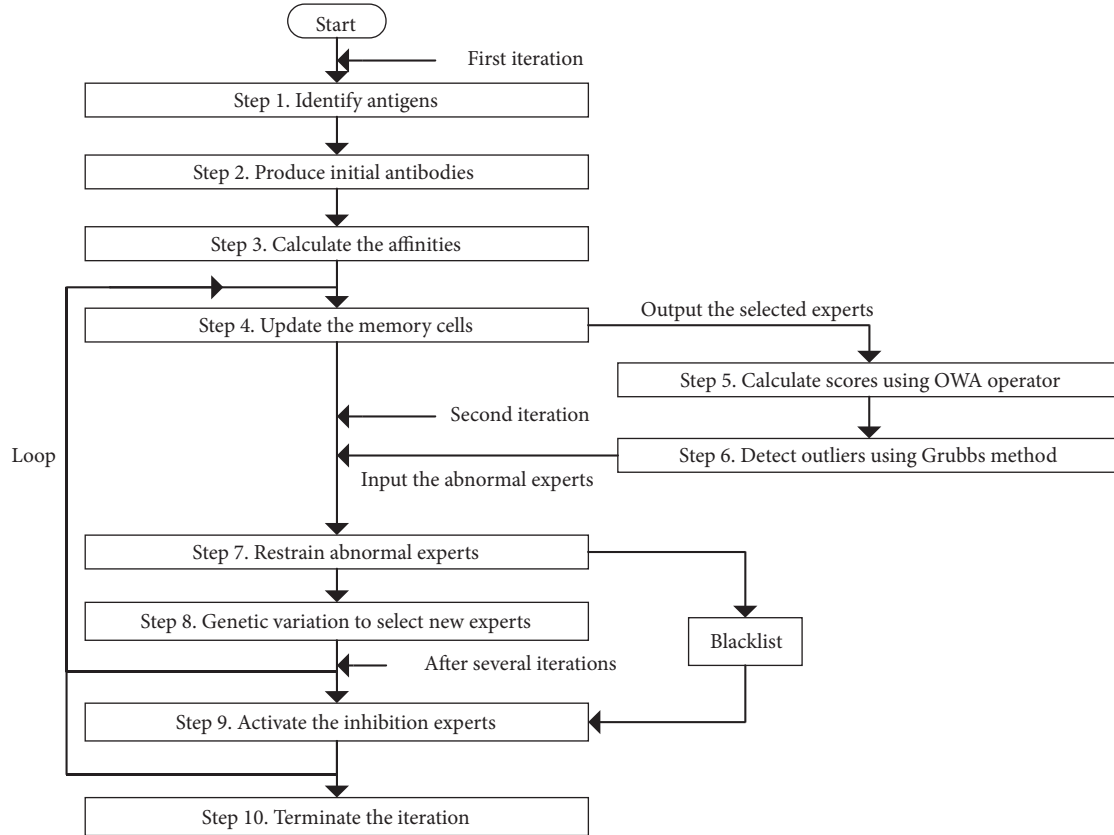


FIGURE 2: Flowchart for the proposed algorithm.

TABLE 1: Initial values for the 30 experts.

Expert ID	Value	Expert ID	Value	Expert ID	Value
01	89	11	94	21	90
02	86	12	93	22	96
03	87	13	92	23	88
04	98	14	85	24	84
05	85	15	87	25	86
06	84	16	86	26	87
07	86	17	90	27	95
08	80	18	92	28	92
09	84	19	91	29	91
10	87	20	84	30	83

Step 1: Identify the antigens. The objective function in each iteration was to select five appropriate experts. The constraint conditions were that all experts to be selected were normal.

Step 2: Produce the initial antibodies. The 30 experts were treated as the initial antibodies and their expert IDs taken as their unique identifiers.

Step 3: Calculate the affinities. At the first iteration, the affinity was the initial value of each expert and no expert was marked. In the subsequent iteration, if an abnormal expert was marked, then $tag_i = 1$. Each expert had at most 3 three chances to be marked as it was necessary to consider the contingencies in the scoring process. The values for the abnormal tags were defined as follows:

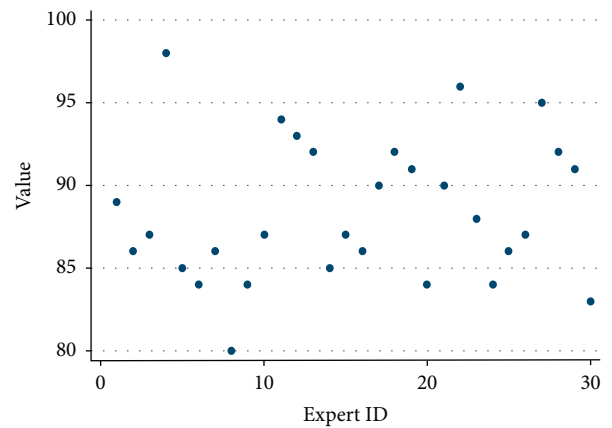


FIGURE 3: The scattergram of initial values for the 30 experts.

$$V_{tag_i} = \begin{cases} = 5 & tag_1 = 1 \\ = 10 & tag_2 = 1, \\ = 15 & tag_3 = 1 \end{cases} \quad (1 \leq i \leq 3). \quad (15)$$

Step 4: Update the memory cells. The affinities for the 30 experts were ranked in descending order and the top five experts put into the memory cells. In this case, the IDs = {04, 22, 27, 11, 12} of five experts were selected. These experts were then output to participate in the bidding evaluation.

TABLE 2: Selected expert IDs using RS.

Project ID	Expert ID	Expert ID	Expert ID	Expert ID	Expert ID
1	25	15	29	30	03
2	12	13	23	18	05
3	15	17	28	08	24
4	25	24	10	23	28
5	08	21	25	14	02

TABLE 3: Selected expert IDs using IEA.

Iterations number	Expert ID	Expert ID	Expert ID	Expert ID	Expert ID
1	04	22	27	11	12
2	03	23	28	11	13
3	03	24	29	11	13
4	03	25	29	10	13
5	03	25	29	10	121

Step 5: Calculate the scores using the OWA operator. The five experts provided their individual preferences for a public furniture purchase project, the scores for which are shown in Table 4. The scores were reordered in descending order according to the different bidders.

Using equations (5) and (6); $n = 5, \mu_5 = 3,$ and $\sigma_5 = \sqrt{2}$.

Then from equation (8), the weights for each expert were determined as $w_1 = 0.1117, w_2 = 0.2365, w_3 = 0.3036, w_4 = 0.2365, w_5 = 0.1117$

The OWA operator was then utilized to adjust the weights for the reordered scores; for example, the final score for A1 bidder was

$$\begin{aligned}
 OWA_w(A1) &= w_1 \times 97.96 + w_2 \times 92.96 + w_3 \times 92.96 + w_4 \times 89.96 + w_5 \times 89.46 \\
 &= 0.1117 \times 97.96 + 0.2365 \times 92.96 + 0.3036 \times 92.96 + 0.2365 \times 89.96 + 0.1117 \times 89.46 \\
 &= 92.42.
 \end{aligned}
 \tag{16}$$

Table 4 shows that, compared to the averaging method, the use of the OWA operator changed the final results; that is, the first and second places for the winning supplier were swapped.

Step 6: Detect the outliers using Grubbs method. Using equations (12) and (10), the average values and the standard deviations were calculated, as shown in Table 5. Then, using equation (11), the Grubbs statistic values were determined (Table 6).

From the Grubbs method threshold, when $n = 5$ with a confidence interval of 90% in Table 7, G_n for expert 22 was determined to be 1.63. As this was larger than 1.602, expert 22 was classified as abnormal and therefore marked $tag_1 = 1$. The affinity of expert 22 was $Fitness(22) = 96 - 5 = 91$.

Step 7: Restrain the abnormal experts. Starting from the second iteration, the value of each expert was judged. With the given threshold set at 80, if the affinity < 80, the marked experts were added to the blacklist, new experts were added, and the memory cells were updated.

Step 8: Genetic variation to select new experts. At the second iteration, $P_m = 0.5$ and $f = 88.4$. The genetic variation resulted in new IDs = {05, 22, 26, 10, 13}. As can be seen, expert ID 22 was again selected; however,

the affinity was reduced from 96 to 91. Steps 4 to 8 were then repeated four times.

The results for the five projects are shown in Table 8. Suppose that expert 22 was marked each time and no other experts were marked in the following 1–4 iterations. By the fifth iteration, as the affinity of expert 22 was reduced to 66, this expert was added to the blacklist and the memory cells were updated.

Step 9: activate the inhibition experts. The experts in the blacklist were activated after 10 iterations, and the tag reset $tag_i = 0$.

Step 10: Terminate the iteration. When there were no more projects that needed to select experts, the iterations stopped.

4.2. Discussion. The following conclusions were made from the experimental results. First, compared to the RS and IEA, the proposed algorithm was effectively able to limit abnormal expert selection because of the punishment mechanism. As shown in Table 8, as expert ID 22 was detected as abnormal three times, they were placed on the blacklist and not invited to join the bidding evaluations.

TABLE 4: Scores from the five experts and the final calculated results.

Bidder	Expert 4	Expert 22	Expert 27	Expert 11	Expert 12	Average score	Scores with OWA
A1	92.96	97.96	89.96	89.46	92.96	92.66	92.42↓
A2	86	84	80	78	79	81.4	81.16
A3	90	94	95	93	91	92.6	92.65↑

TABLE 5: Average values and standard deviations from the Grubbs method.

Bidder	Average value (μ)	Standard deviation (s)
A1	92.42	3.39
A2	91.16	3.45
A3	92.65	2.07

TABLE 6: The G_n values for the Grubbs test statistic.

Bidder	G_n				
	Expert 4	Expert 22	Expert 27	Expert 11	Expert 12
A1	0.16	1.63	0.72	0.87	0.16
A2	1.40	0.82	0.37	0.92	0.63
A3	1.28	0.65	1.13	0.17	0.80

TABLE 7: Grubbs statistic method threshold.

n	90.00%	95.00%	97.50%	99.00%	99.50%
3	1.148	1.453	1.155	1.155	1.155
4	1.425	1.463	1.481	1.492	1.496
5	1.602	1.672	1.715	1.749	1.764
6	1.729	1.822	1.887	1.944	1.973
7	1.828	1.938	2.020	2.097	2.139
8	1.909	2.032	2.126	2.221	2.274
9	1.977	2.110	2.215	2.323	2.387
10	2.036	2.176	2.290	2.410	2.482

TABLE 8: Selected expert IDs using the proposed algorithm.

Iterations number	Expert ID	Expert ID	Expert ID	Expert ID	Expert ID
1	04	22	27	11	12
2	05	22	26	10	13
3	06	22	26	10	13
4	07	23	25	11	13
5	07	22	26	11	12

Second, unlike the average method, the OWA operator caused a change in the final result by adjusting the weights of the bidding scores; in other words, when two bidders' average scores are very close, the one that has the smaller standard deviation wins. For instance, the standard deviation for bidder A1 was 3.39 and the standard deviation for bidder A3 was 2.07. Relative to bidder A1, the scores for the bidder A3 were similar to the mean, which meant that the winning supplier was different when the OWA operator was applied, clearly indicating that the OWA operator was able to successfully identify the controversial bidder and select the bidder that had a better comprehensive level; in other words, as the OWA operator effectively restrained the weights of the abnormal experts in the scoring process, fairer results were guaranteed.

5. Conclusions

As public procurement is complex and uncertain, it is vital that expert selection is as transparent and efficient as possible, especially for e-procurement. This paper explored the feasibility of using an IEA to select experts, an OWA operator to adjust the expert weights, and Grubbs statistical method to identify the outliers. By introducing historical records into the expert selection process, the proposed algorithm was found to successfully identify doubtful/abnormal experts. The algorithm in this paper also has some shortcomings, especially for the group experts biased to one supplier; it does not play a large role in restraining the experts. Future research aims to explore the development of a more reasonable punishment mechanism for expert selection. For example, design a more equitable distribution of

the weighting factors for the scoring process, develop better scoring criteria for public procurement, or improve public procurement bidding evaluation fairness in big data environments using machine-learning algorithms.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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