Research Article

A Framework for Online Reverse Auction Based on Market Maker Learning with a Risk-Averse Buyer

Hojat Tayaran and Mehdi Ghazanfari

School of Industrial Engineering, Iran University of Science and Technology, Tehran, Iran

Correspondence should be addressed to Mehdi Ghazanfari; mehdi@iust.ac.ir

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The online reverse auction is considered as a new e-commerce approach to purchasing and procuring goods and materials in the supply chain. With the rapid and ever-expanding development of information technology as well as the increasing usage of the Internet around the world, the use of an online reverse auction method to provide the required items by organizations has increased. Accordingly, in this paper, a new framework for the online reverse auction process is provided that takes both sides of the procurement process, namely, buyer and seller. The proposed process is a multiattribute semisealed multiround online reverse auction. The main feature of the proposed process is that an online market maker facilitates the seller's bidding process by the estimation of the buyer's scoring function. For this purpose, a multilayer perceptron neural network was used to estimate the scoring function. In this case, in addition to hiding the buyer's scoring function, sellers can improve their bids using the estimated scoring function and a nonlinear multiobjective optimization model. The NSGA II algorithm has been used to solve the seller model. To evaluate the proposed model, the auction process is simulated by considering three scoring functions (additive, multiplicative, and risk-aversion) and two types of open and semisealed auctions. The simulation results show that the efficiency of the proposed model is not significantly different from the open auction, and in addition, unlike the open auction, the buyer information was not disclosed.

1. Introduction

An essential aspect of supply chain systems which is extensively discussed in the literature is the procurement of the required materials and logistics. In this regard, the reverse auction method in the supply chain management is used to select the best suppliers for the procurement [1]. More precisely, a reverse auction has a similar structure to a forward auction with the difference that, in a reverse auction, a buyer requests several potential suppliers/sellers to make their bids to sell one or more products. Then, the buyer investigates the bids and selects one or more suppliers [2]. The growth of e-commerce since the late 1990s significantly enhanced the use of online environments to organize reverse auctions. Many companies employ electronic reverse auction platforms to supply their products. The use of this approach has resulted in significant savings in comparison to other common

product supply approaches, particularly in business-to-business (B2B) procedures [3]. Thus, different companies and researchers have developed online platforms with different features to facilitate the execution of reverse auctions.

Despite the advantages of online reverse auctions, the experience shows that the transaction sides become less willing to use online reverse auctions after a while [4, 5]. Some of the reasons for this unwillingness are

- (1) Online reverse auction focuses on buyer's preferences and ignores seller's preferences. In other words, sellers often do not have the opportunity to improve their bids in an auction, while buyers have multiple alternatives from different sellers to optimize their purchases [6].
- (2) Sellers need a multiround process to have the opportunity to improve their bids. In this case, they can

optimize their bid in the new round, based on buyer's feedback in the previous round. However, due to the buyer's privacy, information is generally not provided to him other than the seller's rank or rating, so there is little possibility of optimizing the bid.

Accordingly, this study attempts to propose a mechanism that incorporates the challenges mentioned above and finds solutions to mitigate or solve them. In the proposed model, in addition to selecting the best bid by the buyer, sellers also have the opportunity to improve their bid and utility in a multi-period process based on the limited disclosed information. Information is disclosed in such a way that the privacy of both the buyer and the seller is maintained.

In summary, a major difference between the current study and other multiattribute reverse auction studies such as [7–12] is the information disclosure mechanism. In the proposed model, an online auction service provider (OASP), as an interface between the buyer and seller, estimates the buyer's scoring function. It then provides this information to the seller to optimize their offer using the proposed new optimization model. OASP employs a multilayer perceptron neural network to predict a buyer scoring function and sellers solve a nonlinear mathematical programming model using the NSGAI multiobjective genetic algorithm.

The remainder of this paper is organized as follows. In Section 2, the review of literature related to multiattribute reverse auction modeling is carried out. In Section 3, the main problem is described, and then, in Section 4, in a simulated environment, several numerical examples are presented to compare the different revelation policies and scoring functions. Finally, in Section 5, the overall conclusion of the paper and suggestions for future research are presented.

2. Literature Review

An auction problem can have several characteristics. In a general classification, Teich et al. [13] have divided the characteristics of an auction into 16 categories by reviewing the literature (Table 1). Since the proposed model in this paper is structured based on multiattribute reverse auction, research related to this structure has been considered in this section.

The multiattribute reverse auction can be categorized based on either the buyer's problem, the seller's problem, number of rounds of the auction, number of attributes, or the type of disclosure of the buyer's or seller's information. Some studies have focused on both the buyer and the seller side [14–20] while in some research [21–25] only the buyer's side has been taken into consideration. On the one hand, the aim of buyer's problem is generally seeking to maximize the expected scoring function [15, 19, 25, 26], maximizing the buyer's utility [14, 17, 23], maximizing auction performance [18], minimizing purchase costs [20], or maximizing the probability of winner determination in the next round [22]. On the other hand, the seller's problem in a competitive condition is considered by equilibrium solutions such as the Bayesian game [15]. In monopoly conditions, the maximization of utility [14, 19] or profit [17] is considered as the problem of seller. It should be noted that reverse auctions

can be single-round [7, 18–20, 25, 26], two-round [23], or multiround [14, 15, 17, 22]. In most cases, more rounds in the auction process can help to find the optimal price for the buyer's side and also increase the level of competition between sellers. It can be conducted on the basis of the information provided to sellers in each round. Therefore, the level of information disclosure is an influential factor in assessing the performance of an auction [27].

When it comes to the information disclosure in the reverse auction, it can be divided into three categories: (1) the disclosure of seller's information for other sellers, (2) the disclosure of seller's information for the buyer, and (3) the disclosure of buyer's information for sellers. The disclosure of seller's information for other sellers mainly includes the information about the bids and the rank of each seller. At most real auctions, the reverse auction is executed in a sealed form. It means that the sellers' information is not disclosed and the result of the ranking is privately announced to sellers [7, 19, 20, 22, 23, 25]. However, it has been seen in some research [14, 17, 18] that this process has been considered openly. In [15], to model the Bayesian games, the cost distribution function of the seller is revealed for other sellers.

Also, in real conditions, some information such as cost function and how to determine the bid is not generally available to the buyer. The sealed type of disclosure for seller's information to the buyer is taken into consideration by [7, 15, 17, 20, 23, 25]. However, in some studies, the information such as the seller's cost function [18], the parametric form of the seller's cost function [14], the level of attributes for the previous winner of the bid, the threshold level for nonprice attributes and the relative importance of previous attributes [22], and the distribution function of bids [19] has been revealed to the buyer. Buyer's information that can be revealed in a reverse auction process for sellers is related to how the buyer prioritizes or scores sellers. Therefore, in some research, it is assumed that the sellers have complete information on how to prioritize or score the buyer [15, 18, 20], while in others, no information is provided from the buyer to sellers [14, 22, 25].

Some studies have tried to develop a mechanism for providing information to sellers that are able to improve their bids. For example, in [23], buyers propose their attributes in two groups as competitive information (private information) as well as generic ones to the seller. In [23], the seller's problem has not been investigated, and since the algorithm for determining the level of information disclosure is dependent on the seller's bids, the interactive relationship between the sellers and the buyer has been neglected. In another study of [17] in each round, sellers, using information about other sellers bids and their scores, predict the buyer's utility function (weights of the utility function) and, by solving a mathematical programming model with the objective of maximizing profit, submit their new bids. In this study, the buyer's scoring function is considered as the L_α metric distance function and the process of forecasting does not allow the use of other scoring functions.

In the present paper, a multiattribute multiround online reverse auction model is provided. In the proposed model, in addition to simultaneously modeling the buyer's and seller's

TABLE 1: Classification of auction types.

No.	Feature	Description
1	Number of items of a good	One or more goods
2	Nature of goods	Homogenous/heterogeneous
3	Attributes	One or more attributes
4	Type of auction	Forward/reverse
5	Nature of auction	One-round/multiround
6	English vs. Dutch auction	Ascending/descending price
7	Participants	Invitation/open
8	Market maker	Exist/does not exist
9	The price paid by the winner	First price/second price/etc.
10	Is price discrimination applied?	Yes/no
11	Do constraints exist?	Explicitly/implicitly
12	Is there a follow-up negotiation?	Yes/no
13	Is a value function elicited for the buyer?	Yes/no
14	Nature of bids	Open/semisealed/sealed
15	Are bids divisible?	Yes/no
16	Are bundle bids allowed?	Yes/no

problems, without disclosing the seller's information to other sellers, a level of buyer's information is revealed to sellers. In this framework, an online market maker who organizes an auction on an online platform estimates the buyer's scoring function in each round and gives it to sellers. The estimation of the scoring function is made using the artificial neural network, and it is possible to predict this function independently of the type of buyer's scoring function. The estimation of the scoring function is based on the information acquired from the previous buyer's auction information on the online platform (if any) as well as the information obtained from the previous round of auction. In Table 2, the summary of research related to multiattribute reverse auctions, as well as the suggested model of this research (last line), is presented.

3. Problem definition

The structure of a reverse auction is remarkably differentiated from the forward auction. In the forward auction, the buyer offers his/her bid to sellers, who aim to sell their products such as artworks and antiques, to select the best bid. In contrast, in a reverse auction, sellers offer their bids to the buyer that they should choose the best bidder to buy their product. The proposed framework of this research is based on a single product multiround multiattribute reverse auction. Participation in the auction process is free, and the auction is managed by a marketer, which is here called the Online Auction Service Provider (OASP). In the proposed approach, OASP plays an essential role. In each round of the auction process, OASP provides an estimate of the buyer's priority function to the seller in order to offer more effective bids in the next round. Figure 1 shows the information flow of the auction process.

Moreover, Figure 2 describes the process of each flow between the buyer, the OASP, and the sellers.

A market maker as an intermediary has a history of buyers' records in auction operations. Hence, if the buyer does not make a change in his scoring function, the market maker can use a better estimation of the scoring function

using the buyer's past auction data. If a seller uses the auction platform for the first time, determining the auction winners will be postponed for more rounds (for example, the second round) to obtain sufficient data to fit the scoring function. In this case, it is sometimes possible to resample the data obtained from the initial round. In the following, we describe the mathematical formulation of the auction process.

Suppose there are n sellers, K attributes, and one buyer. The seller i will give OASP a bid vector $S_i^j = (a_{i1}^j, \dots, a_{ik}^j)$ in each round until announcing the end of the auction and determining the winner, where a_{ik}^j is attribute k of seller i in round j . In the first round, each seller will provide an initial bid on the OASP platform based on his/her capabilities. This bid is made available to the buyer by OASP. In this formulation, in order to calculate the seller's score by the buyer, three scenarios are considered. The problems that the buyer, OASP, and seller face are discussed in Figure 2 as follows.

3.1. Buyer's Problem. Buyer in each round, after receiving bids $S_i^j = (a_{i1}^j, \dots, a_{ik}^j)$, calculates the score of each seller. Here, three types of scoring functions are calculated by the buyer: the additive scoring function, the multiplicative scoring function, and the risk-aversion scoring function.

3.1.1. Additive and Multiplicative Scoring Function. In the additive scoring function, the scoring of sellers is based on the weighted sum of the values for the attributes (equation (1)) and the multiplicative scoring function is based on the product of the attributes (equation (2)):

$$\text{Score}_i^j = \sum_{k=1}^K w_k a_{ik}^j, \quad (1)$$

$$\text{Score}_i^j = \prod_{k=1}^K (1 + w_k a_{ik}^j) - 1, \quad (2)$$

where w_k is the weight of the k^{th} attribute.

TABLE 2: Researches related to the multiattribute reverse auction and proposed model.

Reference	Buyer problem	Seller problem	The number of rounds	The number of attributes	Disclosure of buyer's information	Disclosure of seller's information	
						For other sellers	Buyer
[15]	Determining the highest score by the scoring function	Equilibrium solution for bayesian games	Multiround	Two	Open	Cost distribution function	Sealed
[14]	Predicting the cost function of sellers by using reverse optimization and maximizing utility	Utility function	Multiround	Two or more	Sealed	Open	Estimating the parametric form of the cost function
[18]	Maximizing the efficiency	Maximizing the efficiency	Single-round	Two or more	Open	Open	Cost function
[23]	Data envelopment analysis model with goal of maximizing utility function	—	Two-round	Two or more	The function of prioritizing in first round and private attributes in second round	Sealed	Sealed
[22]	The data envelopment analysis model aims to maximize the probability of determining the winner in the next round	—	Multiround	Two or more	Sealed	Sealed	Providing the level of attributes for previous winning bids, minimum threshold levels for noncompetitive attributes, and the relative importance of attributes by the online platform
[19]	Maximizing the expected score	Maximizing expected utility	Single-round	Two	Scoring distribution function	Sealed	Bids distribution function
[17]	Maximizing the utility function	Maximizing the profit	Multiround	Two or more	Estimation of the L_α metric scoring function based on previous scores	Sealed	Sealed
[7]	Fuzzy minimization of cost of purchase (price) and expected delivery time difference, with proposed delivery time and objective function of the seller	Profit maximization considering the satisfaction of the constraints on the seller's production program	Single-round	Two or more	Master production schedule	Sealed	Sealed
[20]	Minimizing the purchase costs	Maximizing the profit	Single-round	Two or more	Open	Sealed	Sealed
[16]	Maximizing the utility function	Maximizing the utility function	Multiround	Two or more	Sealed	Sealed	Sealed
[26]	Maximizing the score by BOCR-uRTODIM framework	—	Single-round	Two or more	Sealed	Sealed	Sealed
[21]	Maximizing the payoff based on evolutionary game	—	Multiround	Two or more	Sealed	Sealed	Sealed

TABLE 2: Continued.

Reference	Buyer problem	Seller problem	The number of rounds	The number of attributes	Disclosure of buyer's information	Disclosure of seller's information
						For other sellers
						Buyer
The current paper	Determining the highest score by the scoring function	Profit maximization and minimizing the distance to the ideal buyer's bid	Multiround	Two or more	Estimation of scoring function by online auction service provider using artificial neural network	Sealed
						Sealed

FIGURE 1: Information flow of the proposed auction model.

3.1.2. Risk-Aversion Scoring Function. In this scenario, the behavior of a risk-averse buyer is defined based on the prospect theory [28]. In this case, the buyer specifies the ideal

value $S_i^{j*} = (a_{i1}^{j*}, \dots, a_{ik}^{j*})$ for each of the attributes. First, each of the bids is converted into a risk-aversion bid by

$$A_{ik}^j = \begin{cases} (a_{ik}^j - a_{ik}^{j*})^\alpha, & a_{ik}^j - a_{ik}^{j*} \geq 0, \\ -\theta(a_{ik}^{j*} - a_{ik}^j)^\beta, & a_{ik}^j - a_{ik}^{j*} < 0. \end{cases} \quad (3)$$

In equation (3), $0 < \alpha < 1$ and $0 < \beta < 1$ is the profit and loss parameters, respectively. θ indicates the buyer's risk behavior. $\theta > 1$ represents risk-aversion, $0 < \theta < 1$ is risk seeking and $\theta = 1$ is risk-neutral behavior of the buyer. Similar to equation (3), the initial score is obtained from

$$\text{iScore}_i^j = \sum_{k=1}^K w_k A_{ik}^j. \quad (4)$$

Since it is probable to obtain a negative score, the final score is calculated by

$$\text{Score}_i^j = \begin{cases} \text{iScore}_i^j - \min\{\text{iScore}_i^j, i = 1, \dots, n\} + 1, & \min\{\text{iScore}_i^j, i = 1, \dots, n\} < 0, \\ \text{iScore}_i^j + \min\{\text{iScore}_i^j, i = 1, \dots, n\} + 1, & \min\{\text{iScore}_i^j, i = 1, \dots, n\} > 0. \end{cases} \quad (5)$$

3.1.3. OASP Problem. After calculating the score of each seller, the obtained information is given to OASP. OASP estimates the buyer's scoring function using a multilayer perceptron neural network. The structure of estimating the buyer's scoring function using the neural network is shown in Figure 3. In this structure, the seller's bid information up to round j is the input of the model, and the target is the score of bids. Training of the neural network, OASP provides the function $\text{net}^j(S_i^j)$ to improve seller's bids.

3.1.4. Seller's Problem. The seller uses the estimation of the scoring function performed by OASP to determine its new bid. The problem of determining a new bid for a seller in the j^{th} round is designed as equations (6)–(9):

$$\max \pi_i^j = a_{i1}^j - C(S_i^j), \quad (6)$$

$$\min d_i = |\text{net}^j(S_i^j) - \text{net}^j(S_i^{j*})|, \quad (7)$$

$$\text{s.t. } \text{net}^j(S_i^j) \geq \text{net}^j(S_i^{j-k}), \quad \text{for } k = 1, \dots, j-1, \quad (8)$$

$$\underline{a}_{ik}^j \leq a_{ik}^j \leq \overline{a}_{ik}^j, \quad \text{for } k = 1, \dots, K. \quad (9)$$

Assuming that a_{i1}^j is the proposed price in the j^{th} round, the objective function in equation (6), i.e., π_i^j of seller i , should be maximized, where $C(S_i^j)$ is the cost function of the bid S_i^j . Additionally, the objective function in equation (7), the distance between the estimation of the current bid score, and the ideal score from the buyer's point of view S_i^{j*} are minimized. Ideal bid S_i^{j*} is the upper bound of attribute a_{ik}^j for the positive attributes and the lower bound is for the negative attributes. Sellers use these values if the buyer offers their ideal values for each attribute; otherwise, each seller uses its estimation for the ideal buyer's value. Constraint (8) states that the estimated score for the current bid must be higher than the score in the previous round. Constraint (9) indicates the bounds of the buyer's ability to provide an attribute, where $\underline{a}_{ik}^j$ is the lower bound and $\overline{a}_{ik}^j$ is the upper bound of attribute a_{ik}^j .

FIGURE 2: Problem under investigation.

FIGURE 3: Structure of the estimation of the buyer's scoring function using the neural network.

4. Model Assessments

In order to evaluate the mathematical model, the proposed auction process is simulated by taking into account several sellers and a buyer. For this purpose, the MATLAB software version 2016 has been used. The main purpose of the simulation is to evaluate the performance of the model in different situations. Evaluation is carried out in two ways:

- (1) The disclosure of buyer's scoring function for sellers (an open auction)
- (2) The estimation of the scoring function by OASP (a semisealed auction)

For each of these two auctions, three types of additive, multiplicative, and risk-aversion scoring functions are considered. In the open auction, the problem of the seller is defined as follows:

$$\begin{aligned}
 \max \quad & \pi_i^j = a_{i1}^j - C(S_i^j), \\
 \min \quad & d_i = |\text{Score}(S_i^j) - \text{Score}(S_i^{*j})|, \\
 \text{s.t.} \quad & \text{Score}(S_i^j) \geq \text{Score}(S_i^{j-k}), \\
 & a_{i1}^j - C(S_i^j) > 0, \\
 & \underline{a}_{ik}^j \leq a_{ik}^j \leq \overline{a}_{ik}^j.
 \end{aligned} \tag{10}$$

The following criteria are also considered as indicators for evaluating the model:

- (1) The average score of the winner
- (2) The average of the winner's profit
- (3) Number of rounds in each auction process

The pseudocode of the simulation process is presented in Table 3.

In Table 4, the related parameters of simulation process including the maximum number of iterations (I), the number of sellers (n), the improvement threshold (Δ), and

TABLE 3: Pseudocode of the simulation process.

Step	Implementation
1	Initialization
1.1	Number of iterations = I
1.2	Number of sellers = n
1.3	Improvement threshold = Δ_T
1.4	$S = 1$
2	Do the steps 3–12 until $S < I$
3	Round(j) = 1
4	Generate n random bids $S_i^j = (a_{i1}^j, \dots, a_{ik}^j)$
5	Compute the Score_i^j for each bid
6	Determine the highest Score_i^j and save it
7	Train a neural network for input $(S_1^j, \dots, S_n^j, S_1^{j-1}, \dots, S_n^{j-1}, S_1^1, \dots, S_n^1)$ and target $(\text{Score}_1^j, \dots, \text{Score}_n^j, \text{Score}_1^{j-1}, \dots, \text{Score}_n^{j-1}, \text{Score}_1^1, \dots, \text{Score}_n^1)$
8	$j + 1 = j$
9	Solve seller problem and obtain n new bids $S_i^{j+1} = (a_{i1}^{j+1}, \dots, a_{ik}^{j+1})$
10	Compute the Score_i^{j+1} for each new bid
11	Determine the highest Score_i^{j+1} and save it
12	If $\Delta = ((\text{Score}_i^{j+1} - \text{Score}_i^j) / \text{Score}_i^j) \geq \Delta_T$ go to 8 otherwise go to 13
13	End

TABLE 4: Simulation parameters.

Description	Parameter	Value
Maximum number of iterations	I	50
Number of sellers	n	6
Improvement threshold	Δ_T	0.05
	θ	2
Risk-aversion cost function	α	0.5
	β	0.5

the parameters of the buyer's risk-aversion scoring (θ, α, β) are presented. The cost function of equation (6) is considered as the weight combination for the attributes, that is, $C(S_i^j) = \sum_{k=1}^K u_k a_{ik}^j$. The unit cost u_k for calculating the seller's cost function, weights w_k , the buyer's scoring functions for each of the attributes, and the ideal bid S_i^{j*} are provided in the Appendix (please see Tables 5 and 6). In each iteration, the values of the parameters in Table 4 as well as the specified parameters (u_k , w_k and S_i^{j*}) are constant, and only the initial selection vector for each bid would be changed.

Also, these constant values are considered for the comparison of the two different types of disclosure for the buyer's function (open and semisealed). It is noteworthy that the three types of buyer's scoring function (additive, multiplicative, and risk-aversion) are assumed the same. The use of nonlinear activation function in the multilayer Perceptron neural network generally has higher performance [29]; hence, the activation function $\tanh(x)$ is used to map the input and the target variable. Therefore, the function $\text{net}^j(\cdot)$ is nonlinear, and consequently, problems (6)–(9) are a nonlinear two-objective model due to the objective function (7) and constraint (8). Here, the NSGAI multiobjective genetic algorithm is used to solve the seller's problem. Since the solutions of the model are obtained as the Pareto optimal frontier, the profit (first objective function) is prioritized to select the optimal solution from the Pareto frontier. The hidden layer size for the neural network (the number of hidden layer neurons) is 10 and the neural network learning

TABLE 5: Attribute's unit cost and ideal bid level for each sellers.

Parameter	Seller 1	Seller 2	Seller 3	Seller 4	Seller 5	Seller 6
u_2	0.47	0.42	0.27	0.25	0.14	0.29
u_3	0.54	0.36	0.68	0.48	0.59	0.18
u_4	0.32	0.27	0.23	0.34	0.20	0.53
S^*	[0, 10]					

TABLE 6: Buyer-scoring function weights.

w_1	w_2	w_3	w_4
0.25	0.20	0.25	0.30

function is Levenberg–Marquardt. For the NSGAI algorithm, the population size is 200, the crossover ratio is 0.8, and the Pareto ratio is 0.35.

4.1. Simulation Results. In this section, the results of the simulation process are presented. Tables 7–9 show one simulation iteration for an open auction, using the additive, multiplicative, and risk-aversion functions, respectively.

In the first round, the vector of the bid is the same for all the situations. In each table, the seller who has earned the highest score is marked in bold. For example, in Table 7, which belongs to the open auction results with an additive function, in the first round, the sixth seller obtained the highest score. Then, in the second round, sellers have solved their problems, and eventually, the fifth seller has earned the highest score. As can be seen, the scores for all sellers have been upgraded. Since $\Delta = 0.066$ is larger than the threshold $\Delta_T = 0.05$, the auction goes to the next round. In the third round, the improvement of score $\Delta = 0.0046$ is lower than the threshold, and so the auction process is stopped. The winner of the auction is the fifth seller.

As demonstrated in Table 7, the profit of the fifth seller in the second round has risen alongside the first round. Therefore, for this seller, there was a possibility to

TABLE 7: Results of the first iteration of simulation for open auction and additive scoring function.

First round					Second round					Third round								
Seller	Attributes				Seller's score	Seller's profit	Attributes				Seller's score	Seller's profit	Attributes				Seller's score	Seller's profit
	1	2	3	4			1	2	3	4			1	2	3	4		
1	6	5	1	2	2.850	2.449	9.934	0.946	2.084	7.162	2.875	6.024	9.976	0.081	1.259	8.464	2.876	6.497
2	8	2	1	6	2.950	5.117	9.973	1.367	4.646	5.028	2.950	6.296	9.952	0.166	4.671	6.045	3.027	6.488
3	8	2	6	3	3.300	2.614	9.985	7.155	0.145	7.389	3.688	6.186	9.991	5.814	0.100	8.331	3.689	6.368
4	5	2	2	2	2.750	2.829	9.985	2.790	0.610	6.790	2.751	6.639	9.999	6.250	0.319	4.735	2.750	6.629
5	8	5	2	5	3.500	5.067	10.000	7.212	1.597	6.480	3.786	6.684	9.944	4.759	1.519	8.193	3.803	6.663
6	7	2	6	3	3.550	3.708	9.998	7.436	6.811	1.195	3.550	5.939	9.986	7.095	8.222	0.238	3.550	6.281
	Δ				—		Δ				0.066		Δ				0.0046	

TABLE 8: Results of the first iteration of simulation for open auction and multiplicative scoring function.

First round				Second round			
Seller	Attributes				Seller's score	Seller's profit	Seller's profit
	1	2	3	4			
1	6	5	1	2	7.00	2.449	5.889
2	8	2	1	6	6.35	5.117	6.164
3	8	2	6	3	8.98	2.614	4.011
4	5	2	2	2	6.56	2.829	6.364
5	8	5	2	5	10.25	5.067	8.000
6	7	2	6	3	10.64	3.708	7.000
Δ				—			

TABLE 9: Results of the first iteration of simulation for open auction and risk-aversion scoring function.

First round				Second round				Third round			
Seller	Attributes				Seller's score	Seller's profit	Seller's profit	Attributes			
	1	2	3	4				1	2	3	4
1	6	5	1	2	2.507	2.449	9.984	0.095	0.044	8.027	3.007
2	8	2	1	6	2.341	5.117	9.994	0.944	0.559	7.941	3.841
3	8	2	6	3	2.464	2.614	9.976	8.351	0.007	3.727	3.964
4	5	2	2	2	2.568	2.829	9.993	8.709	0.040	4.101	2.568
5	8	5	2	5	2.536	5.067	10.000	8.040	0.001	4.741	4.036
6	7	2	6	3	2.714	3.708	9.999	1.482	9.988	0.791	3.714
Δ				—				Δ			

simultaneously improve the offer and profit in the second round. In Table 8, which belongs to the open auction with a multiplicative function, the sixth seller is identified as the winner of the auction in the first round. Sellers 5 and 6 have not been able to improve the bids for the foreseeable future, but other sellers have upgraded their bids. Table 9 shows the open auction results with a risk-aversion function. Similar to the two previous scoring types, in the first round, the best seller's bid is the sixth. In the second round, the fifth seller offered the best bid. Given that $\Delta = 0.486$, the sellers have presented their new bids. In the third round, none of the sellers have been able to improve their bids, and $\Delta = 0$. Therefore, the winner seller is the fifth seller.

Before running a semisealed auction simulation, assuming that the seller has a history of using the auction platform for a specified product with given attributes, a multilayer perceptron neural network is trained with 100

random bids for each scoring function (100 bids with their scores). In each round, new information (new bids and new scores) is added to the previous dataset, and the network is then retrained. Tables 10–12 show the results for the semisealed auction. In Table 10, the results of the semisealed auction are presented with the additive scoring function.

Herein, similar to the open auction, the sixth seller wins the first round. In the second round, the highest score belongs to the sixth seller, but in the third round, the fifth seller obtains the highest score, and as the improvement in the next round is less than the threshold, the fifth seller is announced as the winner. As can be seen, by comparing two auctions with additive scoring functions, the final score of the winning seller in the semisealed auction is higher, and the profit of winning seller is lower than that of the open auction. Table 11 summarizes the results of a semisealed auction with a multiplicative scoring function. Similar to the

TABLE 10: Results of the first iteration of simulation for semisealed auction and additive scoring function.

First round				Second round				Third round				Fourth round				Seller's profit	Seller's score	Seller's profit	Seller's score				
Attributes				Attributes				Attributes				Attributes											
Seller	1	2	3	4	1	2	3	4	Seller's score	Seller's profit	1	2	3	4	Seller's score	Seller's profit	1	2	3	4			
1	6	5	1	2	2.449	10.000	0.327	0.846	8.604	5.358	6.584	9.980	1.493	8.245	9.989	7.851	1.546	9.980	1.493	8.245	9.989	7.851	1.546
2	8	2	1	6	5.117	9.815	2.533	3.051	5.445	5.356	6.112	10.000	0.698	9.475	9.514	7.863	3.588	10.000	0.698	9.475	9.514	7.863	3.588
3	8	2	6	3	2.614	9.968	4.652	0.399	7.544	5.785	6.642	9.968	4.652	0.399	7.544	5.785	6.642	9.968	4.652	0.399	7.544	5.785	6.642
4	5	2	2	2	2.829	9.993	0.592	0.012	8.755	5.246	6.816	10.000	9.530	1.889	9.556	7.745	3.372	10.000	9.530	1.889	9.556	7.745	3.372
5	8	5	2	5	5.067	9.991	7.370	0.078	6.731	6.010	7.498	9.995	8.760	5.307	9.769	8.508	3.581	9.995	8.760	5.307	9.769	8.508	3.581
6	7	2	6	3	2.449	9.996	0.684	9.191	3.713	6.048	6.584	9.996	0.684	9.191	3.713	6.048	6.584	9.966	0.041	0.028	0.026	2.515	1.546
Δ					-			Δ		0.703			Δ			0.406			Δ			0	

TABLE 12: Results of the first iteration of simulation for semisealed auction and risk-aversion scoring function.

First round							Second round					
Seller	Attributes				Seller's score	Seller's profit	Attributes				Seller's score	Seller's profit
	1	2	3	4			1	2	3	4		
1	6	5	1	2	2.507	2.449	6.00	5.00	1.00	2.00	2.507	2.449
2	8	2	1	6	2.341	5.117	8.00	2.00	1.00	6.00	2.341	5.117
3	8	2	6	3	2.464	2.614	8.00	2.00	6.00	3.00	2.464	2.614
4	5	2	2	2	2.568	2.829	5.00	2.00	2.00	2.00	2.568	2.829
5	8	5	2	5	2.536	5.067	8.00	5.00	2.00	5.00	2.536	5.067
6	7	2	6	3	2.714	3.708	7.00	2.00	6.00	3.00	2.714	3.708
Δ	—	Δ	0									

TABLE 13: The results of the Mann–Whitney U test for comparing the open auction and the semisealed auction in each of the scoring functions.

Scoring function	Criterion	Mann–Whitney U test statistics	p -value	Results
Additive	Winner's profit	1.6477	0.0994	There is no significant difference
	Winner's score	0.2665	0.7899	There is no significant difference
	The number of auction rounds	0.4175	0.6763	There is no significant difference
Multiplicative	Winner's profit	−0.7281	0.4666	There is no significant difference
	Winner's score	−0.9506	0.3418	There is no significant difference
	The number of auction rounds	−0.6868	0.4922	There is no significant difference
Risk-aversion	Winner's profit	−3.4391	0	There is a significant difference
	Winner's score	−1.0338	0.3012	There is no significant difference
	The number of auction rounds	−3.1171	0.0018	There is a significant difference

open auction, the sixth seller is the winner of the auction. In the third round, none of the sellers have the ability to improve the bid, and thus, the winner is determined in the second round of the auction. Similarly, the final score of the winning seller in semisealed is greater, and the profit of the winner is less than those in the open auction. In Table 12, the semisealed auction results are presented with a risk-aversion scoring function. After the first round, sellers have not been able to improve their bids, and so the sixth seller with the highest score in the first round has been set as the winner of the auction. Unlike additive and multiplicative scoring, in the semisealed auction with risk-aversion scoring, the winner's score is greater, and the winner's profit is less than those in the open auction.

After the completion of the simulation process, the average winning seller score, average profit of winning seller, and the average number of rounds of the auction in both open and semisealed auctions, as well as three types of additive scoring, multiplicative scoring, and risk-aversion scoring are compared. To this end, nonparametric Mann–Whitney U test or Wilcoxon rank tests are used to compare the open and semisealed auctions, and also, the Kruskal–Wallis test is devised to compare three types of scoring functions. These two tests are equivalent to t -test and one-way ANOVA in parametric conditions and are based on the median of two independent populations. The null hypothesis of both tests is the equality of the medians of the two populations. An alternative hypothesis in the Kruskal–Wallis test is the inequality between at least one pair of populations. For large samples, the Mann–Whitney U test statistic follows the normal distribution, and the Kruskal–Wallis test statistic follows the chi2 distribution with

$N - 1$ degrees of freedom, where N is the number of samples.

Table 13 shows the results of the Mann–Whitney U test for comparing the open and semisealed auctions in each of the scoring functions. As can be seen, at 95% confidence level, there is a significant difference between the two types of the open and semisealed auctions only in the risk-aversion scoring function, and in the winning seller's profit and the number of rounds of the auction. In the risk-aversion scoring, the average profit in a semisealed auction is less than that in the open auction, and according to the test result, this difference is almost significant. On the contrary, the average number of auction rounds in a semisealed auction is considerably higher than that in the open auction, taking into account the risk-aversion scoring function.

In Table 14, the results of the Kruskal–Wallis test are presented to compare three scoring functions in each of the open and semisealed auctions. As can be seen, there is a meaningful difference in the confidence level of 95% between the profit of winning seller in the three types of the scoring function, either in an open auction or a semisealed auction; however, this distinction is not strong in a semisealed auction (p -value is close to 0.05). In the open auction, a significant difference is found between the average profits of the winning seller in the three scoring functions. The highest median profit belongs to the multiplicative scoring (9.77), then the additive scoring (6.503), and, finally, the risk-aversion scoring (4.802). According to results obtained from the Kruskal–Wallis test, in Table 14, the difference between the average profits of the winning seller for all scoring functions is significant. The highest average profit in the open auction belongs to the multiplicative scoring

TABLE 14: The comparison of results obtained from the Kruskal–Wallis test for multiplicative, additive, and risk-aversion scoring in the open and semisealed auction.

Type of auction	Criterion	Kruskal–Wallis test statistics	p -value	Results
Open	Winner's profit	31.74	0	There is a significant difference
	The number of auction rounds	14.33	0.0008	There is no significant difference
Semisealed	Winner's profit	8.32	0.0156	There is a significant difference
	The number of auction rounds	2.5	0.2866	There is no significant difference

(7.750), then the risk-aversion scoring (4.3181), and finally, the additive scoring (4.2330).

The results of the model show that, in both open and semisealed auctions, the utility of the buyer and the seller along with the number of auction rounds under the additive and multiplicative scoring functions are not significantly different. Hence, in the semisealed auction, in addition to no disclosure of the main buyer's scoring function for the seller and the OASP, an appropriate approximation of this function by OASP is provided to improve the seller's bids during the auction. On the contrary, the use of the multiplicative scoring function has gained higher profits for the seller. This is true for both open and semisealed auctions as well.

5. Conclusion

Regarding the importance and wide application of online auctions, in this paper, a multiround multiattribute online reverse auction in an e-commerce framework was proposed. The main feature of the proposed model, in comparison with other models, is the design of an information disclosure mechanism that allows the improvement of sellers' bids in each round of auction, while also considering the information privacy of buyers and sellers. In this model, an online auction service provider estimates the buyer's scoring function and makes it available to sellers. Based on this estimated function, sellers optimize their bid by solving a nonlinear optimization model. The process of bidding will continue until a stopping condition, that is, a predefined improvement in the score of the best bid is achieved. In order to evaluate the proposed model, the auction process was simulated. In this simulation, three scoring functions, additive, multiplicative, and risk-aversion, were considered for the buyer. Also, the simulation was performed in two types: open (seller knows the buyer's scoring function) and semisealed (the proposed model). The simulation results show that, in both open and semisealed auctions, the utility of the buyer and the seller, as well as the number of auction rounds, with considering the additive and multiplicative scoring functions, was not significantly different.

Dráb et al. [27] with a statistical study of 11,000 online reverse auctions have shown that disclosure of information leads to increased auction efficiency, but buyers and sellers are less willing to participate in an open auction. In the proposed model of this paper, in addition to the fact that there is no concern about explicit disclosure of information, the efficiency of the auction has not changed significantly compared to the open type. There is very little research on the limited disclosure of buyer information. Saroop et al.

[23] have designed a mechanism to explicitly disclose the scoring weights of some of the criteria in the second round of the auction. In the proposed model of this paper, there is no explicit disclosure of scoring weights. Also, Karakaya and Köksalan [17] assumed the L_α metric scoring function for the buyer and provided an estimate of this function for sellers, but based on our proposed model, it is possible to estimate different scoring functions using neural networks.

When it comes to the direction for future research, the proposed framework for online auctions can be developed in many ways. The proposed framework of this article can be used in the auction processes with a single attribute, or with some items of a specific product/service. Moreover, different curve fitting methods such as regression and support vector regression can be employed to fit the scoring function and evaluate their performance. The use of new multiple-attribute decision-making methods such as the proposed method in [30] can be considered to model the buyer's side (buyer selection) in combination with the model presented in this article.

Data Availability

All data used to support the findings of this study are included in the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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