

Bid Pricing Based on the Learning Curve Method for Internet Bid Systems

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Introduction (1/3)

- In internet bid systems, sellers set bid prices when selling items are registered for bidding
- The bidding can be unsuccessful if the bid price is unreasonably high compared with the normal price
- The successful bid with a loss can be made when a seller carelessly provides too low bid price
- So, an unsuitable bid price is one of the main reasons that bidding becomes unsuccessful

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Introduction (2/3)

- If a seller provides too high a bid price compared with the normal price, it can decrease his/her own successful bid rate
- The successful bid with too low a price may make no profit or a loss in the sale
- So, pricing agents that generate adequate bid prices for sellers based on the past selling history data and the costing methods can be helpful

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Introduction (3/3)

- In this paper
 - Design and implement a bid pricing agent that generates bid prices for sellers based on costing methods such as the high-low point method, the scatter diagram method, and the learning curve method
 - In order to obtain appropriate profit without a loss in bidding, we can decide a bid price using the agent
 - Also, we can decrease unsuccessful biddings with too high price to obtain a lot of profit

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Related Work & Costing Methods (1/2)

- Related Work
 - Design and Implement of a Policy-oriented Matching Agent System for E-Commerce
 - Design and Implement of a Intelligent Agent based on Margin Push Multi-agent System for Internet Auction
 - use the past successful bid price, the auction time etc.
 - Estimate price for buyer based on the past buying history data
 - the price is used for buyer and is not used for seller

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Related Work & Costing Methods (2/2)

- Costing Methods
 - High-low Point Method
 - connect the highest point value to the lowest point value among the past cost data in a straight line
 - Scatter Diagram Method
 - decide relation the cost with the operating rate according to opinion of assayer as way supporting high-low point method
 - Learning Curve Method
 - represent the learning effect that the business production become higher as workers repeat fixed work continually

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Design of a Bid Pricing Agent (1/5)

- Generating the Bid Price

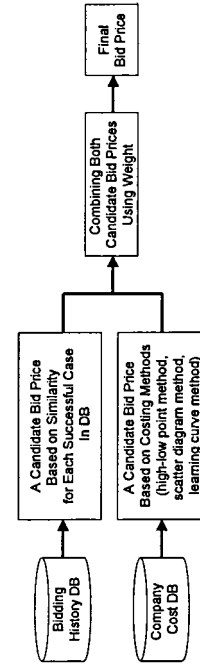


Figure 1. Bid Pricing Procedure

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Design of a Bid Pricing Agent (2/5)

Generating the Bid Price (cont.)

$$P_{bid-price} = w_1 \times P_{total-cost} + w_2 \times P_{bid-history}$$

Where, $P_{bid-price}$ = the final bid price, $P_{total-cost}$ = the candidate bid price based on costing method, $P_{bid-history}$ = the candidate bid price based on history database, w_1 and w_2 are weights ($w_1 + w_2 = 1$).

$$P_{bid-history} = \left(\frac{1}{n} \sum_{i=1}^n w_i \cdot P_i \right) \times Q_{unit}$$

Where, n = the number of similar cases, w_i = the weight of i -th case, P_i = the unit bid price of i -th case, and Q_{unit} = quantity.

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Design of a Bid Pricing Agent (3/5)

Costing Method

$$P_{total-cost} = a + b \times Q_{unit}$$

Where, $P_{total-cost}$ = the total cost, a = the fixed unit cost, b = the variable unit cost, and Q_{unit} = quantity.

High-low Point Method

$$b = \frac{P_{total-max} - P_{total-min}}{Q_{max} - Q_{min}}, \quad a = P_{total-min} - (b \times Q_{min})$$

1) Where, b = the variable unit cost, $P_{total-max}$ = the highest total cost, $P_{total-min}$ = the lowest total cost, Q_{max} = the highest quantity, and Q_{min} = the lowest quantity.

2) Where, a = the fixed unit cost, b = the variable unit cost, $P_{total-max}$ = the highest total cost or the lowest total cost, and Q_{min} = the highest quantity or the lowest quantity.

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Design of a Bid Pricing Agent (4/5)

Scatter Diagram Method

$$\sigma^2 = \frac{1}{n} \sum_{i=1}^n (P_i - m)^2$$

Where, σ^2 = the standard deviation, n = the number of distributed cost, P_i = the distributed cost of i -th case, and m = the average of distributed costs.

Learning Curve Method

$$\sum_{i=1}^n P_i = na + b \sum_{i=1}^n Q_i, \quad \sum_{i=1}^n Q_i P_i = a \sum_{i=1}^n Q_i + b \sum_{i=1}^n Q_i^2$$

Where, P_i = the average accumulative unit cost, Q_i = the accumulative quantity, a = the fixed unit cost, b = the variable unit cost, n = the number of distributed cost.

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Design of a Bid Pricing Agent (5/5)

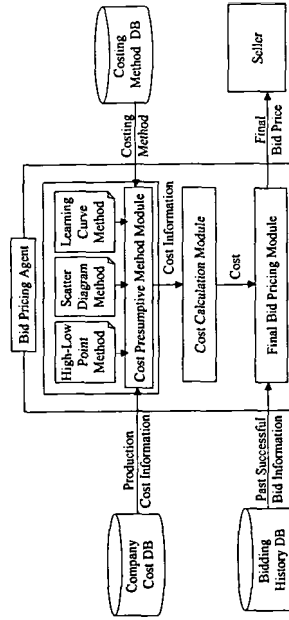


Figure 2. Bid Pricing Agent Structure

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Performance Experiment (1/6)

- Performance Experimental Environment
 - Use the total cost, the total selling quantity, the selling price, etc. of 15 inch TFT-LCD notebook monitor
 - Simulate 120 cases
 - Analyze the successful bid possibility and the expected profit for seller
 - Provide a bid price by a bid pricing agent using each costing method
 - Develop a bid pricing agent with Visual Basic 6.0

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Performance Experiment (2/6)

- Performance Experimental Environment (cont.)
 - Compare the difference between the real cost and the calculated cost based on costing method
 - Use the adjusted MAE (Mean Absolute Error) measures as shown

$$\bar{E} = \frac{1}{n} \sum_{i=1}^n |p_i - m_i| / f_i$$

Where, n = the number of items, f_i = the real cost, m_i = the calculated cost based on costing method.

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Performance Experiment (3/6)

- Comparison of the Error

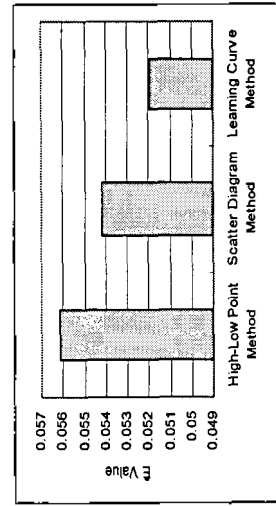


Figure 3. Comparison of E Value

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Performance Experiment (4/6)

- Comparison of the Successful Bid Rate

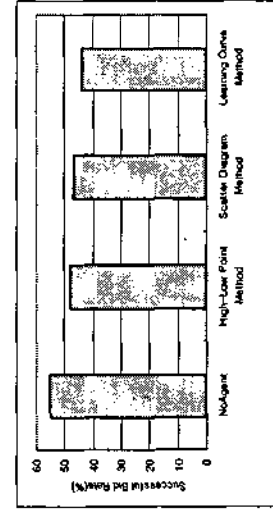


Figure 4. Comparison of Successful Bid Rate : (a) Total Cases

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Performance Experiment (5/6)

- Comparison of the Successful Bid Rate (cont.)

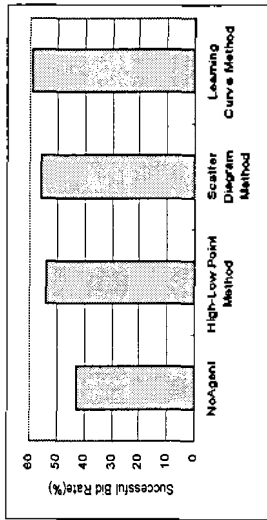


Figure 5. Comparison of Successful Bid Rate : (b) Profit Cases

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Performance Experiment (6/6)

- Comparison of the Successful Bid Rate (cont.)

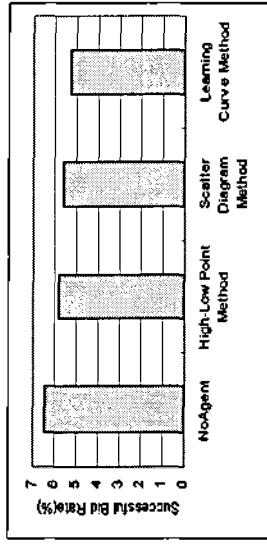


Figure 6. Comparison of Successful Bid Rate : (c) Loss Cases

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Implementation of a Bid Pricing Agent

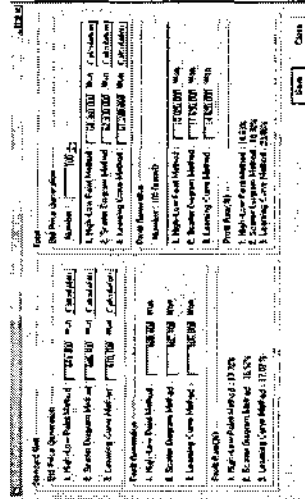


Figure 7. Bid Pricing Window

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Conclusions (1/2)

- Proposed a method that generate bid prices based on costing methods such as the high-low point method, the scatter diagram method, and the learning curve method
- Implemented a bid pricing agent that automatically generates bid prices for sellers
- Evaluated performance of the bid pricing agent using each costing method and showed that the learning curve method had shown the best performance

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Conclusions (2/2)

- Through performance experiments, the successful bid rate with appropriate profit can be increased by preventing sellers from making unreasonable bid prices
- The successful bid rate with loss can be decreased by preventing biddings from becoming successful due to the too low bid price compared to the normal price
- In the future
 - experiment of the pricing agent with a large database of various bidding items

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