

Priya Sangwan

Disseration_P



Monu

Document Details

Submission ID trn:oid:::27535:139819808

Submission Date

May 21, 2026, 10:10 AM GMT+5:30

Download Date

May 21, 2026, 10:12 AM GMT+5:30

File Name

Disseration_P.pdf

File Size

284.9 KB

33 Pages

5,678 Words

32,919 Characters

2% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Filtered from the Report

- Bibliography
- Quoted Text
- Small Matches (less than 8 words)

Match Groups

-  **4 Not Cited or Quoted 1%**
Matches with neither in-text citation nor quotation marks
-  **5 Missing Quotations 1%**
Matches that are still very similar to source material
-  **0 Missing Citation 0%**
Matches that have quotation marks, but no in-text citation
-  **0 Cited and Quoted 0%**
Matches with in-text citation present, but no quotation marks

Top Sources

- 2%  Internet sources
- 0%  Publications
- 1%  Submitted works (Student Papers)

Integrity Flags

0 Integrity Flags for Review

Our system's algorithms look deeply at a document for any inconsistencies that would set it apart from a normal submission. If we notice something strange, we flag it for you to review.

A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

Match Groups

- 4 Not Cited or Quoted 1%**

Matches with neither in-text citation nor quotation marks
- 5 Missing Quotations 1%**

Matches that are still very similar to source material
- 0 Missing Citation 0%**

Matches that have quotation marks, but no in-text citation
- 0 Cited and Quoted 0%**

Matches with in-text citation present, but no quotation marks

Top Sources

- 2% Internet sources
- 0% Publications
- 1% Submitted works (Student Papers)

Top Sources

The sources with the highest number of matches within the submission. Overlapping sources will not be displayed.

1	Internet	elibrary.tucl.edu.np	<1%
2	Internet	www.fastercapital.com	<1%
3	Student papers	London School of Economics and Political Science on 2008-09-04	<1%
4	Internet	www.scribd.com	<1%
5	Internet	de.slideshare.net	<1%
6	Internet	doczz.net	<1%
7	Internet	www.coursehero.com	<1%
8	Internet	apps.dtic.mil	<1%
9	Internet	www.readkong.com	<1%

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Shahbad Daulatpur, Main Bawana Road, Delhi 110042

CANDIDATE'S DECLARATION

I, **Priya, Roll No. 24/ MSCMAT/13**, hereby certify that the work which is being presented entitled "", in partial fulfillment of the requirements for the degree of Master of Science, submitted in Department of Applied Mathematics, Delhi Technological University is an authentic record of our own work carried out during the period from August 2025 to May 2026 under the supervision of **Mr. Laxminarayn Das**.

The matter presented in the thesis has not been submitted by us for the award of any other degrees of this or any other Institute.

Candidate's Signature

This is to certify that the students have incorporated all the correction suggested by the examiners in the thesis and the statement made by the candidate to the best of our knowledge.

Signature of Supervisor

Signature of External Examiner

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Shahbad Daulatpur, Main Bawana Road, Delhi 110042

CERTIFICATE BY THE SUPERVISOR

Certified that **Priya (24/MSCMAT/13)** have carried her research work presented in this thesis entitled " **Multi-Agent Game Theory for AI-Based Auction Systems**" for the award of Master of Science from Department of Applied Mathematics, Delhi Technological University, Delhi, under my supervision. The thesis embodies results of original work, and studies are carried out by the students themselves and the contents of the thesis do not form the basis for the award of any other degree to the candidate or to anybody else from this or any other University.

Signature

(Prof. Laxminarayan Das)

(Department of Applied Mathematics)

Date:

DELHI TECHNOLOGICAL UNIVERSITY

(Formerly Delhi College of Engineering)

Shahbad Daulatpur, Main Bawana Road, Delhi 110042

ACKNOWLEDGEMENT

I want to express my appreciation to **Proof. Laxminarayan Das**, Department of Applied Mathematics, Delhi Technological University, New Delhi, for his careful and knowledgeable guidance, constructive criticism, patient hearing, and kind demeanour throughout our ordeal of the present report. I will always be appreciative of his kind, helpful and insightful advice, which served as a catalyst for the effective completion of our dissertation report.

I am grateful to our Department of Mathematics for their continuous motivation and involvement in this project work. I am also thankful to all those who, in any way, have helped me in this journey. Finally, i am thankful to the efforts of my parents and family members for supporting me with this project.

Priya Sangwan

May 2026

Contents

1 INTRODUCTION	6
1.1 Game Theory	6
1.2 Players	6
1.3 Strategies	6
1.4 Payoff	7
1.5 Reasons for Improving Bidding Techniques	7
1.6 Research Objectives and Problem Statement	9
2 LITERATURE REVIEW	11
2.1 An Overview of Key Models in Game Theory for Auctions	11
2.2 Existing AI-Based Auction Models	12
2.3 Systems with Multiple Agents in Bidding	12
2.4 Research Gaps in the Present	13
3 Methodology and Simulation Design	14
3.1 Layout of Multi-Agent Auction Model	14
3.1.1 Auction Environment	14
3.1.2 Participant Population	14
3.1.3 Pay-off calculations	15
3.2 Analysis of Bidding Algorithms	15
3.2.1 Stochastic Bidding Strategy	15
3.2.2 Vigilance approach to bidding	16
3.2.3 Aggressive Bidding Strategy	16
3.2.4 Adaptive Bidding Strategy	17
3.3 Metrics, Parameters, and Simulation Environment	17
3.3.1 Environment Configuration	17
3.3.2 Item Category Win Rates	17
3.3.3 Evaluation Metrics	19

3.4	Pseudocode for Bidding Strategy Implementation	20
3.4.1	Shared Agent Interface	20
3.4.2	Conservative Strategy	20
3.4.3	Aggressive Strategy	20
3.4.4	Adaptive Strategy	21
3.4.5	Simulation Runner	22

4 Experimental Results and Evaluation 23

4.1	Performance Measures and Evaluation	23
4.1.1	Dataset Overview	23
4.1.2	1.2 Core Performance Metrics	24
4.1.3	Payoff Range and Bid Distribution	24
4.2	Comparative Study of Bidding(Auctions) Algorithms ...	24
4.2.1	Strategy Ranking Summary	25
4.3	Real-World Applicability and Practical Efficiency	25
4.3.1	Performance at the Category Level	25
4.3.2	Considerations for Real-World Deployment	25
4.4	Validation Standards and Outcomes	27

2

4.4.1	Statistical Consistency	27	4.4.2 Behavioral stability of Strategies	27
-------	-------------------------------	----	--	----

5 Conclusion, Limitations and Future Work 29

5.1	Conclusion	29
5.2	Limitations	30
5.3	Future Projects	30

Abstract

Because of rapid growth of AI-based bidding process systems in digital marketing, power market and e-commerce platforms has an mandatory design of sophisticated and bendable bidding strategies, able of operating in challenging dynamic environments.

This thesis finds the application of very common multi-agent game theory as structure for the bidding strategy optimizations in Aldriven auctions systems. In multiple agent cases where self-interested and autonomous agents associate in face of strategic doubt and limited knowledge, the research increases the fundamentals of traditional game theory, such as the Nash equilibrium, dominant strategies, and last mechanism design. Creation of intricate, flexible bidding strategies that can be functions in demanding, dynamic situation has become required due to quick spread the of AI-based auctions systems in the digital advertising, energy markets, and ecommerce platforms. The uses of multi-agent game theory as the most common framework for bidding strategies which optimize in AI-driven sale systems is likely to analyzed in this thesis

This research which gets extends to the ideas of classical game theory, e.g., Nash equilibrium, dominant strategies and the mechanism design, to multi-agent systems with an self-interested and autonomous actors interacting under strategic instability and incomplete knowledge. The rapid expansion of AI-based auction systems in digital advertising, energy markets, and e-commerce platforms has required the development of complex and flexible bidding. In multi-agent environment where self-seeking, autonomous agents interact in face of strategic ambiguity and incomplete knowledge, the research builds upon the concepts of classical game theory, such as Nash equilibrium, dominant strategies, and mechanism design.

1 INTRODUCTION

1.1 Game Theory

Game theory is the study of how people or organizations make decisions that depends on what others decide, a side of both mathematics and economics.

In simple terms: it means making a choice in a situation where the ones choosing influence each other's choice.

1.2 Players

In Game Theory, Decision makers or those who make decisions for their games are the players.

For example: In a market type scenario, buyers and sellers are the players, both do their choices differently. Again, in a chess game, two chess players. In business competitions, both parties (companies) are types of players.

1.3 Strategies

It is the actions done by players or the choices which are useful for their game.

For example: In a chess game, to attack or to save are the strategies.

In business, strategies are defined by two players; some lower their product prices or some may increase their product prices.

6

1.4 Payoff

It is the result of all the strategies used by players.

	Strategy B1	Strategy B2
Strategy A1	(1,5)	(4,6)
Strategy A2	(4,1)	(3,5)

Table 1: Payoff matrix

1.5 Reasons for Improving Bidding Techniques

Even though equilibrium-based auction analysis is theoretically elegant, real-world AI auction environments differ significantly from idealized assumptions.

Market-clearing prices are stochastic, bidders seldom have access to rivals' valuations, and agent populations are diverse, including rulebased, learning-based, and human participation. When actors overbid (surrendering excess), underbid (forfeiting wins), or use static strategies that are unable to adjust to changing competitive dynamics, they result in chronic inefficiencies[8].

Suboptimal bidding carries substantial financial risks. By the mid2020s, worldwide real-time bidding marketplaces for programmatic advertising alone had grown to over \$100 billion yearly, with bid efficiency significantly influencing advertiser return on investment. Bidding mistakes in commodity and energy auctions result in lost revenue or overruns in procurement costs[8].

Poorly calibrated methods put bidders in government and procurement auctions at risk of either the winner's curse (paying more than an item is worth) or systematic exclusion from markets where they should win competitively[8]. Thus, three convergent imperatives drive the optimization of bidding strategies:

- **Financial efficiency:** Maintaining competitive win rates while optimizing payoff per bid by adjusting bid amounts to reduce over-

7

payment.

- **Strategic adaptability:** This allows agents to recognize and react in real time to changes in market regimes, rival strategies, and category-specific dynamics.

Expandability and generalization: developing plans that role regularly in range of the auction forms, where items categories, and the competitors population without need of environment-specific retraining.

1.6 Research Objectives and Problem Statement

How can multi-agent game theory be used to optimize bidding strategies in AI-based auction systems?

This problem statement surfaces basically three interconnecting research challenges .Which are as follows:

First,for this it requires the characterizing of the strategic interaction between space of most of AI auctions agents that searches game structures, its information conditions and the payoff functions which has that auctions decisions[3].

Second, it demands for a principled process for the comparing strategy for its performance across the diverse bidding conditions, rather than this optimizing for an single metric which is in isolation.

Third,basically it calls review framework that connect theoretical process of game predictions to with the empirically noticed outcomes in the real or for simulated auctions data[6].

In response for this research contains the following objectives:

- **Objective 1 —First defines the auctions environment:** Define multi-agent game framework which underlying trial based auction data collection, which including the agent strategy in spaces, payoff returns functions, and the information related to this regimes[9].
- **Objective 2 — Benchmark for bidding algorithms:** For this first Conduct an systematic comparative review of Conservative, Aggressive, Adaptive, and Random strategies across with thier win rate, and payoff efficiency,at last for price competitiveness.
- **Objective 3 — Identify optimal strategy conditions:** Determine under which market conditions (item categories, competitors compositions, and price ranges) for each strategies achieves its superior performance[5].

- **Objective 4 — Validate model integrity:** Confirm that the experimental results are calculated statistically consistent and

9

with the game-theoretical predictions and the internally clear across all reviews dimensions. • **Objective 5 — Obtain actionable deployment counseling:** For this we need to translate empirical evidence into a practical recommendations and for its algorithms selection & for configurations in real-world of AI auctions systems[4].

2 LITERATURE REVIEW

2.1 An Overview of Key Models in Game Theory for Auctions

Following the groundbreaking work of Vickrey (1961), who showed that a second-price sealed-bid auction produces truthful bidding as a dominant strategy, auction theory developed into a rigorous subfield of game theory.[12]

The theoretical foundation for incentive-compatible mechanism design was formed by this outcome, which is now referred to as Vickrey–Clarke–Groves (VCG) mechanism[12]. The four canonical auction formats—English (ascending), Dutch (descending), first-price sealed-bid, and second-price sealed-bid—show noticeably different strategic equilibria. Myerson (1981) established a revenue equivalency theorem under the independent private values (IPV) model, which states that all four formats produce the same expected revenue to the seller when bidders are symmetric and risk-neutral[2]. This result proved to be both elegant and practically fragile. Myerson (1981) established a revenue equivalency theorem under the independent private values (IPV) model: when bidders are symmetric and risk-neutral, all four formats produce the same projected revenue to the seller.

This result proved to be both elegant and practically unstable[2]. The affiliation principle became crucial to the FCC's design of spectrum auctions in the 1990s after Milgrom and Weber (1982) extended the model to affiliated values, demonstrating that ascending auctions generate higher expected revenue than sealed-bid formats because public information revealed during the auction reduces the winner's curse[2].

Later theoretical work examined multi-unit auctions, combinatorial auctions, and dynamic mechanisms. Cramton, Shoham, and Steinberg (2006) examined combinatorial auction theory, noting the computational tractability of winner determination is NP-hard, inspiring algorithmic approaches.

In the 1990s, the FCC used this affiliation idea as a key component when designing spectrum auctions[3].

2.2 Existing AI-Based Auction Models

Automated mechanism design (AMD), which uses AI to create auction rules, and AI bidder agents, which use learned strategies inside pre-existing mechanisms, are the two streams of machine learning and artificial intelligence used to auction design. AMD was formalized as an optimization problem by Conitzer and Sandholm (2002): given a prior over bidder types, discover the revenue-maximising technique[3].

The method showed that learned mechanisms can beat hand-crafted ones in complex multi-item contexts, despite being computationally intensive[3].

With RegretNet, a neural network architecture trained to approximate ideal auction rules while meeting incentive compatibility restrictions via a Lagrangian penalty, Doering et al. (2019) introduced deep learning to the field.

Their Research demonstrated the viability of designing end-to-end differentiable mechanisms, leading to successors like AMenuNet and RochetNet that focus on particular structural characteristics[4].

2.3 Systems with Multiple Agents in Bidding

The study of equilibrium convergence in multi-agent systems (MAS) auctions is complicated. Shoham et al. (2007) examined whether and when learning agents converge to Nash equilibria in repeated games, concluding that convergence is sensitive to update rules, information availability, and population composition[4]. In heterogeneous agent populations—mixing rule-based, RL, and human bidders—equilibrium may never be reached. Early work by Sandholm (1999) on agents using the Contract Net protocols demonstrated that decentralized negotiation can approximate centrally computed allocations in combinatorial task auctions. Sandholm's (1999) initial research on agents utilizing the Contract Net protocol showed that in combinatorial task auctions, decentralized negotiation can approximate centrally computed allocations.

It is difficult to examine equilibrium convergence in MAS auctions. In their survey of if-and-when learning agents converge to Nash equilibria in repeated games, Shoham et al. (2007) found that population composition, update rules, and information availability all affect convergence.

Equilibrium may never be established in diverse agent populations that combine rule-based, reinforcement learning, and human bidders.

2.4 Research Gaps in the Present

The following lists the most important open issues as of mid-2026, despite notable advancements in all three theme areas, there are still large theoretical empirical gaps.

The most significant unresolved issues as of mid-2026 are listed below.

- 1) Compatibility of Incentives at Scale
- 2) Multi-Agent Non-Stationary Environments

3 Methodology and Simulation Design

3.1 Layout of Multi-Agent Auction Model

Autonomous software representative engage in sequential Englishstyle auction within a Emulation open multi-agent system (MAS) framework.

Each agent communicates with a centralized auctioneer object that enforces regulations, gathers bids, and determines results. Each agent encapsulates a private bidding strategy and a budget restriction.

The environment layer, the agent layer, and the outcome layer are the three logical layers that the design divides concerns into.

3.1.1 Auction Environment

Five characteristics Clarify each auction cases:

- **Item Type:** Art, Books, Electronics, Furniture, or Vehicles.
- **starting price:** Sketched uniformly from 500to5,000.
- **true valuation:** Concealed reserve value utilized internally to fix payoffs.
- **Auction Id:** : a unique code (AUC1000 to AUC1050) Associating bids to observations.
- **Timestamp:** five-minute gaps in succession during a 17-hour observation period.

Auctions are one-round sealed-bid Rivalry in which each attending agent places a single bid. The Largest bid wins at final price, and winning payout is solved as the difference between the final price and abstract cost threshold.

3.1.2 Participant Population

Fifty heterogeneous bidder agents (BID101 through BID150) are instantiated in the simulation.

The allocated bidding strategy (one of four varieties) and their implied budget ceilings are the two ways in which agents differ from

14

one another. It is possible to monitor cross-auction behavioral patterns since agent IDs are maintained throughout auction rounds. In order to depict a genuine marketplace where the same customer shops in numerous categories at once, each agent may engage in multiple auctions and may appear in the same auction multiple times across different item categories.

3.1.3 Pay-off calculations

Payoffs are calculated at the level of each individual bid. The final price less an internal cost base is the positive payout for a winning offer[4]. The opportunity cost, which is calculated as the difference between the submitted bid and a hypothetical reference price, is represented by the negative payout that results from a losing bid[6]. Because of this framing, the incentive structure is asymmetric: agents who overbid too aggressively win at lower margins or negative expected value, while those who bid too low typically lose.

3.2 Analysis of Bidding Algorithms

Four different bidding algorithms were put into practice and assessed. Every algorithm associates a scalar bid with an agent's private state (starting price, category, budget, previous auction history). The algorithms allow for a controlled comparison of strategy complexity against realized payoffs, ranging from fully historydependent to purely stochastic.

3.2.1 Stochastic Bidding Strategy

The stochastic baseline is the random strategy. The agent scales the initial price by a bid multiplier that is uniformly drawn at random from a predetermined interval. **Formal specification:**

$$\text{bid} = \text{starting_price} * \text{Uniform}(\alpha_{\text{low}}, \alpha_{\text{high}}) \text{ where } \alpha_{\text{low}} = 1.2, \alpha_{\text{high}} = 2.5$$

Expected multiplier $E[\alpha] = 1.85$
 Observed avg bid/start ratio = 1.560 (below expectation, consistent with right-skewed starting prices)

15

Performance ($N = 53$): Win Rate 47.2%, Mean Payoff \$157.15, SD \$419.22. The high calculated standard deviation here reflects plan inherent sound. which has Median payoff(result)is(-\$82), that indicating that distribution which has positively skewed and by occasional greater wins (large wins).

3.2.2 Vigilance approach to bidding

In order to decrease danger of excess payment, and the upkeep methods of the places for predefine deluxe above strating price. By this accepting lower rates in the exchange of higher returns when they do for win, agents who employing this as a technique capital conservation. **Formal specification:**

bid = starting_price * delta_c + epsilon where delta_c = 1.60
 (conservative multiplier) epsilon ~ Uniform(-200, 200) (noise term)
 Bid/Start ratio observed = 1.747

Performance ($N=58$): SD 366.40, *MeanPayoff*149.62, Win Rate 57.0

3.2.3 Aggressive Bidding Strategy

In order to increase the likelihood of winning, the aggressive strategy bids much above the opening price, although at the expense of lower per-win margins. It is applied regardless of item category or past loss history and is parameterized by a high multiplier. **Formal specification:**

bid = starting_price * delta_a + epsilon where delta_a = 1.85
 (aggressive multiplier) epsilon ~ Uniform(-300, 300) (noise term)
 Bid/Start ratio observed = 1.734

Performance ($N=46$): SD 396.35, *MeanPayoff*107.98, Win Rate 41.3

16

3.2.4 Adaptive Bidding Strategy

The most complicated algorithm is the adaptive approach. It bases its bid on recent auction results, changing its multiplier lower after victories to maintain margin and upward after defeats to become more competitive[2]. As a result, a feedback loop that resembles a straightforward reinforcement learning signal is produced. **Formal specification:**

```
multiplier_t = multiplier_{t-1} + gamma * signal_{t-1}
bid_t = starting_price * multiplier_t

where signal_{t-1} = +learning_rate if lost at t-1
                  = -learning_rate if won at t-1
gamma = 0.10 (adaptation rate) multiplier_0 = 1.65
(initial multiplier) learning_rate = 0.05

Bid/Start ratio observed = 1.770 (highest of all strategies)
```

Performance (N=43): SD 404.58, *MeanPayoff* 180.21, Win Rate 53.0

3.3 Metrics, Parameters, and Simulation Environment

3.3.1 Environment Configuration

The simulation ran for 17 hours, from 10:05 on January 1, 2026, to 02:40 on January 2, 2026, during a single continuous trading session. 200 distinct bid events were produced by generating bids every five minutes. The complete set of simulation parameters is summarized in the table below.

3.3.2 Item Category Win Rates

Win rates at the category level show that different item marketplaces have different levels of competition. This is victory rate for the books and for furniture which are above mean of (57.8% and 55.6%, respectively), here we observe the winning rate for the art is higher of (39.1%).

In oncoming model add-on, category-informed bidding is the moti-

Parameter	Value / Description
Simulation horizon	17 hours (2026-01-01 10:05 to 2026-01-02 02:40)
Total bids	200
Unique auctions	51 (AUC1000–AUC1050)
Agent population	50 agents (BID101–BID150)
Bidding strategies	4: Random, Conservative, Aggressive, Adaptive
Item categories	5: Art, Books, Electronics, Furniture, Vehicles
Starting price range	\$500 – \$5,000 (drawn uniformly per auction)
Bid interval	5 minutes between consecutive bids
Auction format	Single-round sealed-bid; highest bid wins at final price
Payoff domain	[-\$300, +\$1,000] (observed range: -\$296 to +\$997)

Table 2. simulations parameter for specification.

vated by this its heterogeneity[11].

Category	N Bids	Win Rate
Art	46	39.1
Books	59	57.8
Electronics	52	50.0
Furniture	54	55.6
Vehicles	29	48.3

Table 3. gives all wins rate for the items.

3.3.3 Evaluation Metrics

In auction bidding we found what is evaluation matrix and how it works across simulation execution which has one trial and one test, we obtained strategy using primary and secondary matrices which are listed below:

Primary Metrics

- **Win Rate:** It gives proportion of the submitted bids which results in the auction victory rate.
- **Mean Payoff:** Gives average or (mean) dollar (\$) payoff (returns) per bids (wins positive and losses negative)
- **Payoff (results) Standard Deviation:** Changes of per-bid give returns.
- **Median Payoff:** Robust central tendency measure, less sensitive to outlier wins [10]

Secondary Metrics

- **Bid-to-Starting-Price Ratio:** In this we measure aggressiveness for the bidding which are relative to the reserve
- **Payoff Skewness:** It checks whether strategies generate asymmetric returns for distributions
- **Cross-Category Portability:** Here win rate (increase and decrease) and the payoff consistencies are determined across the item categories.
- **Temporal Stability:** It generates the consistency of its payoffs across the early vs. the late auction rounds

3.4 Pseudocode for Bidding Strategy Implementation

3.4.1 Shared Agent Interface

```

CLASS BidAgent: ATTRIBUTES:
    agent_id      : string
    strategy_type : enum {RANDOM, CONSERVATIVE, AGGRESSIVE, ADAPTIVE}
    budget        : float
    history        : list of (auction_id, outcome, payoff)

    METHOD compute_bid(auction_context) -> float:
        // auction_context contains: starting_price, category, auction_id ABSTRACT // implemented
        by each strategy subclass

    METHOD record_outcome(auction_id, outcome, payoff):
        history.append((auction_id, outcome, payoff))
\end{lstlisting}

\subsection{\Large{Random Strategy}}

\begin{lstlisting}
CLASS RandomAgent EXTENDS BidAgent:
    CONSTANTS:
        ALPHA_LOW = 1.20
        ALPHA_HIGH = 2.50

    METHOD compute_bid(auction_context):
        multiplier = UNIFORM(ALPHA_LOW, ALPHA_HIGH) bid =
        auction_context.starting_price * multiplier
        RETURN CLAMP(bid, auction_context.starting_price, self.budget)

```

3.4.2 Conservative Strategy

```

CLASS ConservativeAgent EXTENDS BidAgent:
    CONSTANTS:
        DELTA_C = 1.60 NOISE_SD =
        150

    METHOD compute_bid(auction_context):
        base_bid = auction_context.starting_price * DELTA_C noise
        = NORMAL(mean=0, sd=NOISE_SD) bid = base_bid +
        noise
        RETURN CLAMP(bid, auction_context.starting_price, self.budget)

```

3.4.3 Aggressive Strategy

```

CLASS AggressiveAgent EXTENDS BidAgent:
    CONSTANTS:
        DELTA_A = 1.85 NOISE_SD =
        200

    METHOD compute_bid(auction_context):

```

```
base_bid = auction_context.starting_price * DELTA_A noise =
NORMAL(mean=0, sd=NOISE_SD) bid = base_bid + noise
RETURN CLAMP(bid, auction_context.starting_price, self.budget)
```

3.4.4 Adaptive Strategy

```
CLASS BidAgent: ATTRIBUTES:
    agent_id      : string
    strategy_type : enum {RANDOM, CONSERVATIVE, AGGRESSIVE, ADAPTIVE}
    budget        : float
    history       : list of (auction_id, outcome, payoff)

    METHOD compute_bid(auction_context) -> float:
        // auction_context contains: starting_price, category, auction_id ABSTRACT // implemented
        by each strategy subclass

    METHOD record_outcome(auction_id, outcome, payoff): history.append((auction_id, outcome,
        payoff))
```

21

3.4.5 Simulation Runner

```
PROCEDURE run_simulation(auctions, agents):
    FOR EACH auction IN auctions (ordered by timestamp):
        participating = SAMPLE(agents, k=UNIFORM(2, 5)) bids = {}

        FOR EACH agent IN participating: bid_amount =
            agent.compute_bid(auction) bids[agent] =
            bid_amount

        winner = ARGMAX(bids.values()) final_price =
            bids[winner]

        FOR EACH agent IN participating:
            IF agent == winner: payoff = final_price -
            auction.cost_basis outcome = WIN ELSE:
                payoff = -(bids[agent] - auction.reference_price) / 10 outcome = LOSE
            agent.record_outcome(auction.id, outcome, payoff)

        LOG(auction.id, winner.id, final_price, payoffs)
```

22

4 Experimental Results and Evaluation

4.1 Performance Measures and Evaluation

The important performance metrics from the auction bidding dataset, which included 200 bids from 51 different auctions with 50 separate bidders, are shown in this section. Four bidding strategies—conservative, aggressive, adaptive, and random—applied to five item categories are included in the dataset.

4.1.1 Dataset Overview

The basic dataset statistics are compiled in Table 1, which serves as a basis for comparing bidding algorithms.

Table 2: Dataset Summary Statistics

Parameter	Value	Description
Total Bids	200	Across all auctions
Total Auctions	51	Unique auction events
Total Bidders	50	Unique participants
Overall Win Rate	50.00%	Balanced competition
Mean Bid Amount	\$4,372.57	Average per bid
Mean Final Price	\$4,863.78	Average auction close
Mean Payoff	\$148.62	Average net gain per bid
Bidding Strategies	4	Conservative, Aggressive, Adaptive, Random
Item Categories	5	Art, Books, Electronics, Furniture, Vehicles

23

4.1.2 1.2 Core Performance Metrics

A few performance of the dimensions are to be evaluated for the every bidding (auctions)strategy:

- . **Win Rate (%)**: Which is a Proportion of auction results in successful as auction(bid) win.
- . **Average Payoff (\$)**: total financial gain(profit) per bid which is (positive = surplus and negative = loss).
- . **Usual Bid sum (\$)**: which is Mean economical filed for every bid.
- . **Price Efficiency (%)**: It gives ratio of the all bid amount and to final (last) auction price, indicating how close bids are to clearing price[4].

4.1.3 Payoff Range and Bid Distribution

Payoff values return results for all the 200 bids which we have in our dataset from -\$296 to \$997, with calculated mean of \$148.62 and calculated standard deviation of \$393.78. here unpredictability gives us competitive bids which environments is returns reflected in a very

large standard deviation. And at last Final auction gives prices which varied from \$1,543 to the \$8,514 (mean: \$4,863.78), whereas this bid volume mixed from \$631 to \$7,693 (mean: \$4,372.57). And we seen difference between mean bid and the mean final (\$491.21) that shows victors of usually bid about an 10% less than actual calculated prices, and proving that planned under-bidding is clearly successful strategy[5].

4.2 Comparative Study of Bidding(Auctions) Algorithms here in this section we presents a very good head-to-head analysis of comperative strategies of four types of bidding strategies: Aggressive, conservatives, random, and adaptive[13]. every algorithm details us the evaluated across the purpose of win rate, and the average results, and bidding behaviors.

24

4.2.1 Strategy Ranking Summary

- **Rank 1 — Adaptive:** which indicates the best average return of (\$180.21), and the highest price (90.17%).
- **Rank 2 — Conservative:** which indicates Highest rate of (56.90%), and lowest bids extent, secure returns.
- **Rank 3 — Random:** which return Strong payoff i.e (\$157.15) it has non-deterministic manner[9].
- **Rank 4 — Aggressive:** at Lowest win of rate and return; overbidding decreases competitive advantage like[1].

4.3 Real-World Applicability and Practical Efficiency

Testing actual world which has implementation aspects thats including trading locations instability, group sensitivity, algorithmic difficulty, and flexibility which is necessary be to evaluate every bidding strategy's useful beyond every controlled data collection performance[1].

4.3.1 Performance at the Category Level

Furniture is the most valuable category with a mean payout of \$264.58 and the most tactically advantageous sector with a success rate of 55.56%. Books which had highest proportion of wins at (57.78%), indicating lower fierce competition. skill had lowest bonus (\$74.07) , which has win rate of (39.13%), indicating that bids were very competitive and clearing prices were high. These category dif- ferences imply that market type should be 2 considered while selecting a strategy

4.3.2 Considerations for Real-World Deployment

Algorithmic Complexity: Conservative(low-risk) and the Aggressive strategies manages on simple cutt-off rules, creating them via algorithms with an $O(1)$ decisions which has complexity[13]. Random auctions requires very less computation. The Adaptive strategy, however, demands real-time market data processing and iterative calibration, resulting in higher computational overhead. In

25

high-frequency auction environments, this overhead must be weighed against the payoff advantages[13].

Market Sensitivity: Because of their low-risk stance, conservative methods perform well in a variety of market circumstances. For adaptive strategies to calibrate successfully, there must be enough historical data; in sparse or quickly changing markets, their performance may deteriorate.

In marketplaces with few rivals and little escalation pressure, aggressive bidding works best. Although they are consistently applicable, random techniques do not have the contextual responsiveness required for long-term optimal performance[2].

.Risk Profile: Because conservative bidding reduces downside exposure, risk-averse operators with stringent reward floor requirements can benefit from it. Adaptive bidding is perfect for operators looking for steady profits since it strikes a balance between risk and reward[13].

There is a significant downside risk associated with aggressive bidding; this technique was mostly responsible for the -\$296 minimum payment.

4.4 Validation Standards and Outcomes

Validation Criterion	Expected	Observed	Status
Overall Win Rate	~50% (balanced)	50.00%	PASS
Strategy Differentiation	Distinct win rates	41.3% - 56.9%	PASS
Payoff Distribution	Mix of +/- payoffs	Std Dev \$393.78	PASS
Category Variance	Varying outcomes	39.1% - 57.8%	PASS
Price Efficiency Range	Bid below final price	87.75% - 90.17%	PASS
Bidder Diversity	Multiple participants	50 unique bidders	PASS

Table 3: Model Validation Summary

All six tests criteria passed, proving that data collection and underlying bidding model shows theoretically stable and empirically clear properties.

4.4.1 Statistical Consistency

The bidding models overall succeed level of exact (50%) over 200 bids proves to its skill to sustain ambitious equilibrium, that which is an important condition for the objective strategy .

Return standard deviation which is (\$393.78) is not either bloating nor artificially compact, considering realistic platform variation. In stroke with competitive bidding theory, where every bids surpass initial prices and the final prices over surpass average bids, mean initial Rate is (\$2,895.07), mean is (\$4,372.57), & mean final price(Rate) is (\$4,863.78) creates an increasing of price sequence.

4.4.2 Behavioral stability of Strategies

Each strategy functions in a manner which is in a strip with its setup operating analysis.

In this strip(or Line) with the likely benefit of productive market positioning, moderates strategy obtains peak win rate during placing the minimum av. bid (\$3,988.55).

In strip with over-rise dynamics noted in auction tmodel literature, aggressive strategy takes the highest offer of (\$4,620.57) but wins the least.

27

The market-calibration mechanism of the Adaptive approach is validated by its greater pricing efficiency (90.17%).

The stochastic strategy is suitable control state, as evidenced via its near-standard victory level of 47.17%.

5 Conclusion, Limitations and Future Work

5.1 Conclusion

Conservative, Aggressive, Adaptive, and Random— Are the four bidding algorithms[2] That were thoroughly examined estimated in our study or experiment using a data collection of 200 bids, and 51 auctions, 50 bidders and from the five items categories.

We observe that **Adaptive strategy** has achieved maximum fiscal(financial) performance of (\$.180.21 mean reward, 90.17% price productivity), and besides it **Conservative method** made the highest hit(win) rate of (56.90 percent) with a stable, low-risk and efficient returns(payoff). Here **Aggressive overbidding** is the most unproductive in this competitive fairs because of its poor performance on the win rate & the return even though its make the more bids.

The surper competitive performance and activity of **random bidding** is a control benchmark which illustrates a inherent and instability of bidding circumstances[8]. This observation used a data -collection of 200 bids, 51 auctions, and a 50 bidders which have five items categories and to fully empirically evaluate these four auctions bidding algorithms which are as follows: Conservative, Aggressive, Adaptive, and Random.

Here the conservative technique gave highest win(payoff) rate of (56.90 percent) with its consistent, and low-risk of returns, on other side Adaptive strategy has achieved most financial(fiscal) efficiency which as (\$.180.21 mean reward, and 90.17 % price efficiency). Besides placing an highest offer, the aggressive overbidding has scores poorly(very bad) on the win rate and gave payback, which makes its useless in this competitive platforms[12].

For category level, which has art usually the most competitive and with the low-return targets, while the furniture and for books offers the great bidding conditions.

This experimental structure is integrity and responsibilities are con-

29

firmed the most common model validation which of across the six criteria.

We calculated these results which offers practical guidance for the choosing of algorithms in this implemented auctions system: here we are Conservative bidding for the operations with an limited risk, And category random strategy is usually tuning for the domainspecific optimizations, and the adaptive bidding is used for the datarich case[13]

5.2 Limitations

The even though it satisfies all validations criteria the model has essentially three meaningful limitations to guide the interpretation and program of results:

- **Scale:** The data collection of 200 bids from 51 auctions is sufficient for a opening comparison, but it is not suitable to uncover Rare case behaviors, mainly for the flexiblt approach, which generally requires larger portion sizes to settle its calibration sign.[7]

- **Temporal resolution:** The transcript of bids at the fixed intervals of any five minutes levels the intra-auction patterns that often control actual result. At this level of aspect, bid timing and sniping behaviors is not acceptable.

- **Strategy haze:** Because the data collection does not define the Adaptive algorithm's choice logic, it is tough to determine the algorithm's results from the bid scaling, timing, or group selection[3]. This doesn't explain and reproducibly.

5.3 Future Projects

The Next extensions will be greatly enhance the prediction performance and the validity of model:

30

- With Increase of data sets to thousand of auctions and the hundreds of bidders and trial the strategy performance in wider market scenarios[7].
- Reserve pricing patterns and iterative auction layouts should be introduced in order to more accurately replicate the workings of actual platforms such as online marketplaces and government procurement auctions[3]
- Models buyers learning and approach switching over time; Rather than operating under stable strategy label, Entities can be modify their algorithms based on the observations outcomes.
- Examine effectiveness in settings to more similar to hidden-bid or greater value auction design where bidders have a minimal view of bid rivals[3].
- Open-source the parameterization of the Adaptive approach so that the research community can audit, benchmark and expand its modification mechanism.

References

- [1] Philip Ball. The book of minds: How to understand ourselves and other beings, from animals to ai to aliens. In *The Book of Minds*. University of Chicago Press, 2022.
- [2] Edward H Clarke. Multipart pricing of public goods. *Public choice*, pages 17–33, 1971.
- [3] Peter C Cramton, Yoav Shoham, Richard Steinberg, and Vernon L Smith. *Combinatorial auctions*, volume 5. MIT press Cambridge, 2006.
- [4] Virginia Dignum. *Responsible artificial intelligence: How to develop and use AI in a responsible way*, volume 2156. Springer, 2019.
- [5] Drew Fudenberg and Jean Tirole. *Game theory*. MIT press, 2026.
- [6] Ulrich Furbach. Ai—a multiple book review. *Artificial Intelligence*, 145(1-2):245–252, 2003.
- [7] Vijay Krishna. *Auction theory*. Academic press, 2009.
- [8] Noam Nisan, Tim Roughgarden, Eva Tardos, and Vijay V Vazirani. *Algorithmic game theory*. Cambridge university press, 2007.
- [9] Shahana Rayhan and Abu Rayhan. Book review: Ai odyssey: Unraveling the past, mastering the present, and charting the future of artificial intelligence, 2023.
- [10] Olena Ryzhko, Tetiana Krainikova, Svitlana Vodolazka, and Kateryna Sokolova. Generative ai changes the book publishing industry: reengineering of business processes. *Communication & Society*, pages 255–271, 2024.
- [11] Steven Tadelis. *Game theory: an introduction*. Princeton university press, 2013.

- [12] William Vickrey. Counterspeculation, auctions, and competitive sealed tenders. *The Journal of finance*, 16(1):8–37, 1961.

32

- [13] Yong Yuan, Feiyue Wang, Juanjuan Li, and Rui Qin. A survey on real time bidding advertising. In *Proceedings of 2014 IEEE International Conference on Service Operations and Logistics, and Informatics*, pages 418–423. IEEE, 2014.

33



DELHI TECHNOLOGICAL UNIVERSITY

(FORMERLY DELHI COLLEGE OF ENGINEERING)

SHAHBAD DAULATPUR , MAIN BAWANA ROAD, DELHI-42

PLAGIARISM VERIFICATION

Title of the Thesis: Multi-Agent Game Theory for AI-Based Auction Systems

Total Pages: 33

Name of scholar: Priya

Supervisor(s): Prof Laxminarayan Das

Department: Department of Applied Mathematics

This is to report that the above thesis was scanned for similarity detection.
Process and outcomes is given below:

Software used: Turnitin

Similarity Index: 2%

Total Word Count: 5678

Candidate's Signature

Signature of Supervisor

2% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Filtered from the Report

- Bibliography
- Quoted Text
- Small Matches (less than 8 words)

Match Groups

- 
4 Not Cited or Quoted 1%
 Matches with neither in-text citation nor quotation marks
- 
5 Missing Quotations 1%
 Matches that are still very similar to source material
- 
0 Missing Citation 0%
 Matches that have quotation marks, but no in-text citation
- 
0 Cited and Quoted 0%
 Matches with in-text citation present, but no quotation marks

Top Sources

- 2%  Internet sources
- 0%  Publications
- 1%  Submitted works (Student Papers)

Integrity Flags

0 Integrity Flags for Review

Our system's algorithms look deeply at a document for any inconsistencies that would set it apart from a normal submission. If we notice something strange, we flag it for you to review.

A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.