

Bi-directional Double Auction for Financial Market Simulation

(Extended Abstract)

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ABSTRACT

Typical Double Auction (DA) models assume that trading agents are one-way traders. With this limitation, they cannot directly reflect the fact individual traders in financial markets (the most popular application of double auction) choose their trading directions dynamically. To address this issue, we introduce the Bi-directional Double Auction (BDA) market which is populated by two-way traders. Based on experiments under both static and dynamic settings, we find that the allocative efficiency of a static continuous BDA market comes from rational selection of trading directions and is negatively related to the intelligence of trading strategies. Moreover, we introduce *Kernel* trading strategy designed based on probability density estimation for general DA market. Our experiments show it outperforms some intelligent DA market trading strategies.

Categories and Subject Descriptors

H.4 [Information Systems Applications]: Miscellaneous

Keywords

Double auction, Artificial market, Multi-Agent, Kernel

1. INTRODUCTION

In recent years, computer scientists are increasingly involved in building market systems [5] that often employ double auction (DA) mechanism for its high efficiency of resource allocations. It is well-known that the dominant application of DA is the financial market. In such a market, traders are usually sellers and buyers simultaneously. Hence,

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we introduce a Bi-directional Double Auction (BDA) market model, in which the trading activity of every individual trader can be bi-directional. The selection of trading direction (*buy* or *sell*) is through trading direction algorithms. Then the order price is decided by trading strategies. Meanwhile, we introduce *Kernel* trading strategy designed based on probability density estimation. It significantly outperforms some popular DA trading strategies including ZIC [4] ZIP [1], GD [3] and RE [2] in our experiments.

Our contributions are as follows. (i) We introduce the Bi-directional DA market which is populated by two-way traders. (ii) We create *Dual* and *Bi* trading direction algorithms for the BDA market. (iii) We develop a customisable platform for conducting various computational experiments regarding dynamic DA market. (iv) We reveal interesting properties of the BDA market. (v) We design *Kernel* trading strategy that significantly outperforms several popular existing ones in heterogeneous games.

2. TRADING DIRECTION ALGORITHM

Dual and *Bi* are trading direction algorithms developed in the BDA market. *Dual* mimics the way human traders decide their trading directions in a stock market. *Dual* is intuitive, simple and fast while generating fairly high allocative efficiency (93.6%). In contrast, *Bi* is complicated and resource-demanding. However, it is non-parametric and features learning ability. As a result, it generates higher allocative efficiency (96.1%) than *Dual*.

2.1 Dual

In *Dual*, trading direction are chosen by comparing private valuations with the asset's market prices. Let v be the private valuation of a trader and v_p be the current market price, we introduce α to represent the uncertainty degree of the trader's private valuation. When $v(1 - \alpha) \leq v_p \leq v(1 + \alpha)$, direction decisions are probabilistic because valuation is not definitely higher or lower than the market price. We use sigmoid function to translate $v - v_p$ into a value between 0 and

1 to represent the probability of *buy* denoted by $P(isBuy)$,

$$P(isBuy) = \frac{1}{1 + e^{-\beta \cdot \lambda(v - v_p)}} \quad (1)$$

where $\beta > 0$ is introduced as the trader's risk attitude and λ is a normalization factor. The probability of *sell* is $P(isSell) = 1 - P(isBuy)$. λ is derived by,

$$\frac{1}{1 + e^{-\lambda v \alpha}} = 0.99 \quad (2)$$

Due to the symmetric nature of sigmoid function, $P(isSell)$ reaches the maximum when $v - v_p = -v\alpha$.

2.2 Bi

A bid (ask) from a low (high) valuation trader should have a smaller chance of transaction than that from a high (low) valuation trader as long as the offer is "sensible"¹. Based on this idea, we design *Bi*. In *Bi*, we calculate how likely a new shout at the price of v is going to be transacted by building probability density estimators on transacted shout prices. After each transaction, two probability density functions $\mathcal{K}_a(x)$ and $\mathcal{K}_b(x)$ can be estimated based on the last maximumly m transacted bids and asks up to the ones of the last transaction, respectively. Accordingly, we can compute two cumulative probabilities,

$$P_b(v) = \int_{-\infty}^v \mathcal{K}_b(x) dx \quad (3)$$

$$P_a(v) = \int_v^{\infty} \mathcal{K}_a(x) dx \quad (4)$$

Trading direction is *buy* if $P_b(v) > P_a(v)$ and vice versa.

3. KERNEL TRADING STRATEGY

Kernel trading strategy is also constructed based on $\mathcal{K}_a(x)$ and $\mathcal{K}_b(x)$. Assuming in the last m transactions, the lowest transacted bid price is \underline{b} and the highest transacted ask price is \bar{a} . We define searching spaces for the optimal bid and ask as $[\min(0, \underline{b}(1 - 0.05) - 0.05v), v]$ and $[v, \bar{a}(1 + 0.05) + 0.05v]$ to make the search comprehensive and efficient simultaneously. Moreover, we use $\mathcal{K}'(p)$ to denote the transaction probability of price p on the estimated probability density curve. Thus, the optimal bid b^* or ask a^* can be found by,

$$b^* = \arg \max_{p \in [\min(0, \underline{b}(1 - 0.05) - 0.05v), v]} \mathcal{K}'_b(p) \cdot (v - p) \quad (5)$$

$$a^* = \arg \max_{p \in [v, \bar{a}(1 + 0.05) + 0.05v]} \mathcal{K}'_a(p) \cdot (p - v) \quad (6)$$

Because $\mathcal{K}(x)$ is a probability density function, $\mathcal{K}'(p)$ actually represents a tiny area around p ,

$$\mathcal{K}'(p) = \int_{p-\delta}^{p+\delta} \mathcal{K}(x) dx \quad (7)$$

where the default value of δ is 0.01.

4. EXPERIMENTS

In the framework of the BDA market, we devised many interesting experiments (see Table 1). The static games investigate the efficiency of a static continuous BDA market and profitability of trading strategies. The dynamic

¹An offer is sensible if the bid price is not greater than v or the ask price is not less than v

Features/Game	Efficiency		Efficiency		Static		Dynamic	
	Game 1	Game 2	Game 3	Game 4	Heterogeneous Game	Heterogeneous Game	Game	Game
Game type	Static	Static	Static	Static	Static	Static	Static	Dynamic
News system	Disabled	Disabled	Disabled	Disabled	Disabled	Disabled	Disabled	Enabled
is HOI available	No	No	No	No	No	No	No	Yes
News occurring probability	N/A	N/A	N/A	N/A	N/A	N/A	N/A	0.3
News impact distribution	N/A	N/A	N/A	N/A	N/A	N/A	N/A	Normal(0,4)
Number of days	100	100	100	100	100	100	100	200
Num of rounds/Day	10	10	10	10	10	10	10	50
Total trader population	100	100	100	100	100	240	240	240
Active percentage in each round	100%	100%	100%	100%	100%	100%	100%	30%
Active Percentage perturbation	0%	0%	0%	0%	0%	0%	0%	5%
Normal-Poisson Agent mixing	Disabled	Disabled	Disabled	Disabled	Disabled	Disabled	Disabled	Enabled
Number of groups	1	1	1	2	2	8	8	8
Number of trader in each group	100	100	100	50	50	30	30	30
Grouping criteria	Trading	Valuation	Trading	Trading	Trading	Trading	Trading	Trading
Trading direction algorithm	Dual	Dual	Dual	Dual	Dual	Dual	Dual	Dual
Trading strategy	ZIC	ZIC	Varies	ZIC	Varies	Varies	Varies	Varies
Trader daily entitlements	5	5	5	5	5	5	5	10
Valuation policy	Random	Random	Random	Random	Random	Random	Random	Array
Random valuation setting	Uniform(60,120)							
Array valuation setting	(61,64,68,70,72,74,76,78,79,80,82,83,84,86,88,90,92,93,94,95,							
Iteration	100	100	100	100	100	100	100	20

Table 1: Experiment configuration details

games are designed to simulate real financial market. In static games, we find: 1) The market allocative efficiency largely comes from traders' rational choices of trading directions. As long as the trading direction algorithm is incentive compatible, the market efficiency improves from 69.9% (efficiency of stochastic trading directions) to 93.6%. 2) With rational trading directions, the more intelligent the trading strategies, the less efficient the market. 3) The market is more efficient and stable if traders private valuations are less uncertain. In dynamic games, market provides rational time-series and *Kernel* group's average wealth exceeds that of GD group (2nd best wealth maker) by 1.36%.

5. CONCLUSION

This paper presents the design and implementation of bi-directional double auction market which is developed to simulate a two-way trading financial market. Through experiments, we find that trading direction algorithm is critical to the allocative efficiency of the BDA market and our new *Kernel* trading strategy demonstrates superior performance to others in terms of both making profit in static BDA market and maintaining wealth in dynamic BDA market.

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