Mertacor 2009 Demystified: Strategies and Guidelines for Market Design in TAC

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ABSTRACT

Current global economy involves highly interconnected markets competing with each other for market share and profit. The recent global financial crisis has revived research interest in this competition and has brought out the need for novel, efficient rules. TAC Market Design tournament is one of the first efforts in studying the interaction between opponent stock exchanges. In this paper, we describe our entrant for 2009, Mertacor, and reason about the importance of proper pricing in this global setting.

Categories and Subject Descriptors

I.6 [**Computing Methodologies**]: Simulation and Modeling; J.4 [**Computer Applications**]: Social and Behavioral Sciences—*Economics*

General Terms

Economics

Keywords

Trading Agent Competition, Market Based Control, Double Auction

1. INTRODUCTION

The *double auction* (DA) is an auction where multiple buyers and sellers are able to submit committed offers to buy or sell goods. This type of auction and, more specifically, its continuous form (CDA) is the dominant mechanism used in major stock exchanges to trade various kinds of securities, such as stocks, futures and options. Moreover, the absence of a decision making center along with its high efficiency make the CDA an attractive choice for decentralised control of open systems. Hence, many variants of this mechanism have often been used in practical applications [3, 15].

Nevertheless, a detailed theoretical analysis of the CDA is extremely difficult due to its dynamics and results may not be valid in markets with boundedly rational human agents. This turned the scientists' attention to agent-based models [14], where software agents mimic human trading behavior, and novel rules are automatically designed for the problem at hand, a field known as *automated mechanism design* [2]. The majority of research during previous years has been concentrated on isolated markets, which is not in accordance with current global economy where individual markets are often tightly interconnected. TAC Market Design (or CAT) tournament [1] is one of the first attempts to study this competition among markets trying to attract investors and make profits.

We have been participating in CAT since its beginning, in 2007, with the software agent Mertacor. This paper presents our last year's strategies as well as the reasons behind our design decisions. Moreover, we empirically demonstrate the importance of the pricing policy in our agent's performance and provide some measures we consider to be important for the game. More specifically, Section 2 shortly describes CAT tournament. Our agent's strategies are presented in Section 3. Section 4 provides our empirical results for each of the game's DA trading strategies. Finally, Section 5 concludes this paper.

2. TOURNAMENT DESCRIPTION

The game of CAT comprises a server and two classes of clients, namely traders and specialists. The game organizers manage both the server and the traders, whereas specialists are designed and implemented by the competition entrants.

Each trader has two strategies, a trading strategy and a market selection strategy. The former determines the agent's bidding behavior in the game and follows one of the four popular DA strategies: ZI-C [6], ZIP [1], RE [9], GD [5]. ZI-C agents exhibit zero rationality, selecting their offers randomly from a uniform distribution, but are not allowed to trade at a loss. ZIP traders try to remain competitive in a market by adjusting their profit margin according to current market conditions, using simple machine learning techniques. RE trading agents mimic human behavior on trading, using recent profit as a reward in a learning algorithm. Finally, GD traders consider the history of cleared transactions and submitted offers and form a belief function based on which they select their preferred offers. The market selection strategy is responsible for selecting a profitable market for the trader, treating the selection as an n-armed bandit problem [13].

[1] http://www.marketbasedcontrol.com

Each specialist takes the role of a broker who must effectively design the rules of its market so as to be profitable while at the same time satisfying its customers. There are typically four high-level strategies it should follow: a) the *accepting policy*, determining the offers that will be accepted in the market, b) the *clearing policy*, specifying how and when will accepted offers be cleared (i.e. led to transactions), c) the *pricing policy*, which sets the price of each transaction, d) the *charging policy*, selecting the amount of fees it should charge traders for its services. There are five different fees in the game, namely the *registration fee* for the entrance of the trader in the market, the *information fee* for extra information on offers/transactions in other markets, the *shout fee* for each shout, i.e. offer, submitted, the *transaction fee* for each transaction cleared, and the *profit fee*, which is a percentage of the trader's profit from a transaction.

A game lasts a number of (virtual) trading days, each of which is divided in trading rounds of fixed duration. At the start of the game, each trader, which can be either a buyer or a seller, is endowed with a number of goods to trade, called its *entitlement*, for each of which it has a *private value*. This value corresponds to the highest amount it is willing to pay for a purchase, if it is a buyer, or the lowest amount it can accept for a sale, if it is a seller. At the beginning of each day, specialists announce their fees and traders register with their desired broker. For the remaining of the day, traders are allowed to submit single-unit shouts (called *bids* for buyers and *asks* for sellers), which typically lead to transactions. Specialists are assessed on a daily basis using three equally weighted measures, namely the market share, the profit share and the transaction success rate (TSR). The latter expresses the percentage of offers submitted that result in transactions. A complete specification of CAT rules can be found in [4].

3. MERTACOR 2009

Given this background, in this section we describe our agent's strategies for the setting of 2009 (i.e. constant private values throughout the game and equal demand and supply quantities). More specifically, we provide an analysis of our desired design objectives, which are more important to other researchers than the strategies themselves. We focus on the internal strategies of our specialist (accepting, pricing, clearing policies), which we consider to be much more tightly coupled than the charging policy. Although the latter can certainly help a market strengthen its position in the game, an entrant's primary objective should be the optimization of its internal rules for its traders' welfare.

According to the theory of microeconomics, the aggregate demand and supply curves of a market are expected to meet at a point (pair of price and quantity) called the market's *competitive equilibrium* (CE), where the allocative efficiency (i.e. traders' aggregate profit) is maximized. Buyers (sellers) with private values above (below) the CE's price are called *intra-marginal* (IM) traders, and are the ones that should typically trade in the market, otherwise they are called *extra-marginal* (EM) traders. Hence, in an isolated market, the objective of a specialist is to estimate this point, making sure that only the desirable, intra-marginal traders are allowed to trade. Nevertheless, in a competitive scenario like CAT, a specialist should also consider the quality of the traders it should attract. In a global economy, there is a population with a wide range of private values, so a specialist should ideally identify and match "rich" buyers with "poor" sellers, thus maximizing its profit margin. These traders are the *globally IM* (gIM) traders, i.e. buyers (sellers) with private values above (below) the *global CE* (gCE). The latter is the CE of the equivalent global market where all traders would trade had it not been their splitting due to the existence of multiple markets.

In an efficient global CAT market, each gIM trader has a single trading counterpart with which it should trade according to the theory. However, the segregation caused by the operation of multiple specialists makes their coexistence in the same market difficult, creating arbitrage opportunities. The severity of this effect is increased as the number of markets increases. Moreover, when traders are allowed to enter and leave specialists at will, thin markets face a significant problem in attracting new customers, finding themselves in a worsening situation. Hence, the first priority of a specialist should be the increase of its market share (which can also increase the probability of transactions and its profit share while at the same time charging small fees).

Our specialist achieves this mainly through its pricing policy, which sets the price of all transactions at or, when not possible, close to the gCE price, as estimated by our technique described in [11]. In this way, traders are incentivised to stay in our market, as they are able to obtain a profit approximately equal to their profit in a globally efficient allocation, even though their counterpart may not be present there at that day.

Besides implementing a fair pricing rule, it is important to accept offers in an appropriate fashion. A tight accepting policy increases the TSR but also the risk of missing potential transactions. On the other hand, a loose policy decreases the TSR but can increase transactions' volume. We have selected to combine both approaches in the long term. More specifically, for the first (*luring*) days, when traders' exploration is high and their attraction is much more important than our TSR, Mertacor implements a *self-beating accepting policy*, according to which all shouts are accepted when submitted for the first time during a day, but only self-improving shouts are allowed upon their current active predecessors. For the remaining days, Mertacor enforces a *soft global equilibrium beating accepting policy*: if gp^* is the price of the gCE, then accepted bids should have a price, $p_b \geq (1 - k \cdot stdev) \cdot gp^*$, and accepted asks a price, $p_a \leq (1+k \cdot stdev) \cdot gp^*$, where $stdev$ is the standard deviation of registered traders' last shouts recorded and $k \in [1, 1.5]$ a slack parameter.

Each specialist also faces the problem of imbalance between daily buyer and seller populations, which means that some of the gIM traders in excess remain unsatisfied, having no counterpart to transact with. Our matching policy tries to compensate for this through its two-fold operation. More specifically, if n is the number of our daily traders and M_i is the number of transacted items per trading agent i over the last days, for the first $N = max_i(M_i), i \in \{1, ..., n\}$, rounds our agent clears transactions at the end of each round, operating like a clearing house. For the remaining rounds, clearing is

Table 1: Results for each trading strategy when Mertacor utilizes estimated gCE. APE corresponds to the mean absolute percentage error of each specialist's CE from real gCE. EPPT is the mean equilibrium profit per trade.

	ZIC			**ZIP**			**RE**			**GD**		
	Score	APE	EPPT	Score	APE	EPPT	Score	APE	EPPT	Score	APE	EPPT
cestlavie	0.432	0.059	44.973	0.108	0.345	23.493	0.411	0.059	48.904	**0.535**	**0.042**	**52.113**
CUNY.CS	0.237	0.142	32.505	0.098	0.505	21.898	0.312	0.107	42.478	0.407	0.156	49.430
IAMwildCAT	0.320	0.112	41.895	0.284	0.225	34.390	0.342	0.093	45.855	0.326	0.093	47.628
jackaroo	0.327	0.133	40.957	0.163	0.331	23.933	0.401	0.090	50.800	0.282	0.133	38.154
Mertacor	**0.523**	**0.057**	**60.215**	**0.686**	**0.017**	**46.023**	**0.427**	**0.054**	**52.929**	0.258	0.112	44.702
PSUCAT	0.259	0.117	38.671	0.167	0.236	31.946	0.301	0.085	47.538	0.361	0.060	51.852
UMTac09	0.431	0.066	42.374	0.087	0.325	23.703	0.425	0.066	46.604	0.356	0.064	38.986

Table 2: Results for each trading strategy when Mertacor utilizes real internal CE. APE corresponds to the mean absolute percentage error of each specialist's CE from real gCE. EPPT is the mean equilibrium profit per trade.

	ZIC			**ZIP**			**RE**			**GD**		
	Score	APE	EPPT	Score	APE	EPPT	Score	APE	EPPT	Score	APE	EPPT
cestlavie	**0.478**	**0.045**	44.846	0.159	0.255	29.501	0.429	0.063	51.387	**0.480**	**0.059**	50.345
CUNY.CS	0.255	0.156	31.117	0.173	0.417	29.836	0.348	0.087	46.651	0.401	0.186	48.329
IAMwildCAT	0.309	0.108	39.174	**0.571**	**0.055**	49.895	0.343	0.088	50.391	0.330	0.104	44.125
jackaroo	0.381	0.103	**48.910**	0.187	0.268	29.937	0.436	0.088	**54.985**	0.268	0.162	36.071
Mertacor	0.368	0.052	48.034	0.404	0.056	48.256	0.341	0.073	48.980	0.282	0.098	45.220
PSUCAT	0.240	0.110	34.755	0.381	0.067	**52.242**	0.318	0.077	50.519	0.384	0.074	**51.834**
UMTac09	0.467	0.054	44.446	0.104	0.306	25.426	**0.445**	**0.061**	49.605	0.407	0.064	40.805

continuous, so a transaction is executed as soon as there is a matchable pair of bids and asks. Matching is always performed between highest bids and lowest asks. Hence, for the first part of each day, Mertacor matches "good" gIM traders (i.e. buyers and sellers with the highest and lowest private values respectively, or with the smallest profit margin), and then makes an effort to match the remaining gIM buyers or sellers in excess with IM sellers or buyers respectively.

Finally, our charging policy charges only a small amount of profit fees. This is the only type of fees that allows for fair and discriminatory charging so that each trader's payment is proportional to its shout's price deviation from the gCE price. For the first luring days, no fees are charged. Then, a moving average on our market share determines the appropriateness of charging: if our market share during the previous days increases, then a starting fee of 5% is charged. This process is repeated for the remaining days, using a conservative fee step of 1.5%.

4. EXPERIMENTAL EVALUATION

In [7, 10], the authors have reasoned about the importance of the pricing of transactions when designing a market. However, our main question still remains: in a global economy with highly interconnected stock exchanges, where bidders are free to move between markets for their trades, is it still advisable for a specialist to follow the short-term strategy of targeting for its internal CE, thus disregarding the remaining global population in its pricing policy? In this section, we make a first effort to empirically demonstrate the effect of this type of pricing policies in CAT.

We have conducted a number of experiments to evaluate our specialist's performance against available opponents. Then, we have changed its accepting and pricing policies so that the real, internal CE is used instead of the estimated gCE, and observed corresponding differences. All specialists (cestlavie, CUNY.CS v.1, IAMwildCAT, jackaroo, Mertacor, PSUCAT, UMTac09) were obtained from the TAC agent repository, although we did not manage to run TWBB. Our experiments were repeated for each of the trading strategies in CAT (ZI-C, ZIP, RE, GD). More specifically we have used 200 traders for each experiment, keeping the expected number of traders per specialist similar to that of the games for 2009. Traders' private values were i.i.d. drawn from the same distribution, $U(50, 150)$. All traders follow an ϵ-greedy market selection strategy ($\epsilon = 0.1$, $\alpha = 1$).

Our main evaluation criterion is specialist's game score. Moreover, we have recorded specialists' daily equilibrium prices and have obtained the mean absolute percentage error (APE) of these prices from the gCE price. Finally, although allocative efficiency measures the effectiveness of market rules for a given population of traders, it provides no information on the quality of traders. For this reason, we have decided to incorporate another metric, the *equilibrium profit per trade* (EPPT). More specifically, if (p_j^*, q_j^*) is the CE of a specialist j, and υ_t is the private value of a gIM trader $t, t \in GIM$, then specialist's daily EPPT is:

$$EPPT_j = \frac{\sum_{t \in GIM} |\upsilon_t - p_j^*|}{q_j^*} \tag{1}$$

Table 1 illustrates our results for the gCE case. As can be seen, our specialist achieves the highest score and is also able to attract the most desirable traders, depicted by its mean EPPT, in three of the four cases. However, when facing GD traders, its performance significantly degrades, revealing a vulnerability for these traders, as was also noted in [8] for our previous agents. The opposite holds for CUNY.CS, which performs much better for the GD case. It is important to note that our results for the score metric are different than the competition's finals in 2009, when more entrants are present in the game. Our agent also outperforms its competitors in our experiments with identical strategy mixes to those of CAT 2009 that we ommit here due to lack of space.

To assess the importance of this pricing in our agent's performance, we have repeated the experiments using the specialist's real CE instead of the gCE in its policies. The results are summarized in Table 2. A CE based strategy seems to have an opposite impact on the results, hence Mertacor takes 4^{th}, 2^{nd}, 6^{th}, and 6^{th} place for ZI-C, ZIP, RE, and GD trader populations respectively. Hence, only GD performance is marginally increased.

Nevertheless, a closer look at the values for the mean APE reveals a strong relation between an agent's score and this metric. In all eight cases, the winner of the games had the lowest mean deviation from the gCE price. This is true for other positions as well, with a smaller APE corresponding to a higher score, although differences in specialists' charging policies yield minor deviations from this empirical finding.

After this finding, we can see in Table 1 that Mertacor is not able to coordinate its CE with the gCE for the GD traders, thus explaining its poor performance for this strategy. We believe that this is partly due to our gCE estimation method's significantly lower accuracy for this type of traders [12]. On the other hand, our highly precise estimation for the RE traders leads to the highest of all scores.

5. CONCLUSIONS AND FUTURE WORK

This paper details our agent strategies for 2009 as well as the reasons underlying their implementation. As shown, Mertacor is the winner of all games except for the case of the GD trading strategy, which deserves further investigation.

What's more, we have argued for the importance of the alignment of individual CE prices with their global counterpart. As was analytically demonstrated for our specialist, but also empirically validated for all entrants, it seems that transaction prices settle near the global CE price on the long term. Hence, in the global economy of CAT, the sooner an entrant is able to accurately estimate this point, the stronger is the possibility for a better placement.

As future work, we intend to improve on our policies, especially for the GD case. Trading strategy mix plays a crucial role when designing markets, hence we are interested in studying the impact of corresponding changes to the market's performance, following an evolutionary game theoretical approach. Finally, we would like to investigate the relation between pricing and charging policies and, more specifically, how to optimize fee values with respect to gCE pricing for static and dynamic scenarios.

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