AGENT-HUMAN INTERACTIONS IN THE CONTINUOUS DOUBLE AUCTION, REDUX

Using the OpEx Lab-in-a-Box to explore ZIP and GDX

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Abstract: In 2001, a team of researchers at IBM published a paper in IJCAI which reported on the first experiments that systematically studied the interactions of human traders and software-agent traders in electronic marketplaces running the continuous double auction (CDA) mechanism. IBM found that two software-agent strategies, known as GD and ZIP, consistently outperformed human traders. IBM's results received international press coverage, probably because the CDA is the mechanism that is used in the main electronic trading systems that make up the global financial markets. In 2002, Tesauro & Bredin published details of an extension to GD, which they named GDX, for which they wrote: "We suggest that this algorithm may offer the best performance of any published CDA bidding strategy". To the best of our knowledge, GDX has never been tested against human traders under experimental conditions. In this paper, we report on the first such test: we present detailed analysis of the results from our own replications of IBM's human vs. ZIP experiments and from our world-first experiments that test humans vs. GDX. Our overall findings are that, both when competing against ZIP in pure agent vs. agent experiments and when competing against human traders, GDX's performance is significantly better than the performance of ZIP.

1 INTRODUCTION

At the 2001 International Joint Conference on Artificial Intelligence (IJCAI-01), a team of IBM researchers presented a paper (Das, Hanson, Kephart & Tesauro, 2001) that generated press coverage around the world (e.g. Graham-Rowe, 2001). Das *et al.*'s paper was the first to apply the laboratory methods of experimental economics (e.g. Kagel & Roth, 1997) to the systematic comparative evaluation of adaptive autonomous software-agent "robot" trader strategies, in controlled experiments that pitted the robot traders against human traders in a continuous double auction (CDA) mechanism. The IBM team explored their own robot strategy, a modified form of the Gjerstad-Dickhaut algorithm (Gjerstad & Dickhaut, 1998) which we will refer to as EGD (Extended GD), and a version of the Zero-Intelligence Plus (ZIP) algorithm developed by Cliff at Hewlett-Packard Labs (Cliff & Bruten, 1997). Das *et al.* reported on results from six experiments involving a number of human subjects being pitted against a similar number of a particular type of trading-agent: EGD in four experiments, and ZIP in the remaining two. The results from all six of these experiments were conclusive: the average efficiency of the robot traders, i.e. their ability to enact profitable transactions, was consistently higher than that of the human traders, and this was true for both the trading strategies. The IBM paper concluded with the following memorable passage:

> "[…] the successful demonstration of machine superiority in the CDA and other common auctions could have a much more direct and powerful financial impact—one that might be measured in billions of dollars annually"

Somewhat curiously, in the decade since that paper was first published, as far as we can determine no-one has yet reported on a replication of those results. We speculate here that this is because, back in 2001, to set up an experimental economics laboratory such as that used by the IBM team required a considerable investment. However, as the real cost of personal computers (PCs) and data-networking hardware has fallen dramatically in the

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past ten years, we observed that it is now possible to re-create the necessary laboratory apparatus using low-cost "netbook" PCs for a total cost of only a few thousand dollars. With that motivation, we have designed and implemented an experimental economics laboratory network trading system, where "trader terminal" netbooks communicate with a central "exchange" server, with the potential for multiple instruments to be traded simultaneously in varying quantities, and with every quote in the marketplace, and details of all transactions, written to a database as a single "consolidated tape" record of the trading events (to sub-second timestamp accuracy) over the course of a trading experiment. This trading system, which is called "OpEx" (from *Open Exchange*) will be open-sourced under a creative commons license in the near future (De Luca, forthcoming 2011). In this paper, we report on the use of OpEx to replicate IBM's IJCAI-01 results from testing human traders against ZIP and the most recent evolution in the "GD" class of algorithmic traders: GDX (Tesauro & Bredin, 2002). To the best of our knowledge, these are the first results from testing GDX against humans. We find that our results agree with IBM in the respect that the GDX and ZIP robot traders consistently out-perform the human traders, but our results differ from IBM's in that we find that GDX outperforms ZIP, while in the IBM study ZIP slightly outperforms EGD on average. Our results are also in line with those achieved by Tesauro & Bredin: in pure robot vs. robot competitions, GDX outperforms ZIP and proves to be a major improvement of the original GD algorithm.

2 BACKGROUND

Today, the vast majority of financial products are traded electronically: following exact rules, buyers and sellers, collectively known as *traders*, interact in a common virtual "marketplace" to trade those products. The numerous organisations that are in place to allow electronic trading of financial securities are known as *exchanges*, or sometimes *markets*. The set of rules that define the exchange process between traders on a market forms its *market mechanism*, of which the continuous double auction (CDA) is the most used due to its high efficiency:

> "Markets organised under double-auction trading rules appear to generate competitive outcomes more quickly and reliably than markets organised under any alternative set of trading rules." (Davis & Holt, 1993)

In a CDA, traders can make bids and accept offers asynchronously at any time during the *trading day* (that is, the fixed-duration trading period during which trading is allowed). All the offers are usually publicly visible by all market participants, and a trade is made whenever the outstanding bid is greater than or equal to the outstanding ask. Although it is made up of simple rules, the nonlinearities of the CDA are too complex to be analysed by traditional mathematical methods such as game theory: as a results, researchers have turned to empirical approaches.

In his Nobel-prize-winning work, Vernon Smith (1962) ran several experiments with human traders, and demonstrated that markets governed by the CDA can reach close-to-optimal efficiency. Also, he proved that transaction prices converge to the market's theoretical competitive *equilibrium price*, where the supply and demand curves intersect. Furthermore, he found that if the supply and demand of markets suddenly changed, the transaction prices would rapidly converge to the new equilibrium price. In many of his experiments, Smith studied the dynamics of CDA-based markets by assigning one unit to sell(buy) at no less(more) than a specific price to each of the traders. The price of the unit, known as *limit price*, represents the maximum amount of money l a buyer can spend to buy the unit, or the minimum value c for which a seller can sell the unit. As a consequence, buyers make a *profit* l-p if they buy at a price p that is less than their limit price, whereas sellers make a profit p-c if they sell for a price p higher than their limit price. The limit prices are private, each trader knowing only her limit. The traders interact by quoting the price at which they are willing to trade their units. In Smith's early experiments this happened by speaking the number out loud, thus the public quotes in a CDA are often referred to as *shouts*. A random player is selected every turn to make a shout, and the game finishes after a fixed number of turns. Following the rules of the CDA, a trade occurs when the outstanding bid is greater than or equal to the outstanding ask. Smith measured the performance of a trader in terms of *allocative efficiency*, which is the total profit earned by the trader divided by the *maximum theoretical profit* of that trader, expressed as a percentage. The maximum theoretical profit of a trader is the profit that trader could have made if all the market participants would have traded their units at the theoretical competitive market equilibrium price. A further measure of the performance of a market is the *profit dispersion*: this is defined as the cross-sectional root mean squared difference between the actual profits and the maximum theoretical profits of individual traders. Formally, if a_i is the actual profit earned by trader *i*, and p_i is the theoretical equilibrium profit for that trader, then for a group of *n* traders the profit dispersion is given by:

$$\sqrt{\frac{1}{n}\sum_{i=1}^{n}(a_i - p_i)^2} \quad (1)$$

3 OPEN EXCHANGE

We ran our experiments on *Open Exchange* (OpEx), an experimental algorithmic trading platform developed by De Luca (forthcoming 2011). OpEx was designed to resemble closely the structure and the behaviour of modern commercial financial-market electronic trading systems, and to be generic enough to support experimental economics simulations of arbitrary complexity. Figure 1 illustrates the interaction between the core components in a simple configuration. The connections between the components on the left hand side show the flow of order data. Orders represent the agents' instructions to buy or sell a specific quantity of a given product at a particular price condition. Human traders enter their orders in the Trading GUI, a graphical application that allows users to view the market order book (i.e. the descending-ordered list of currently outstanding bids, and the ascending-ordered list of currently outstanding offers), their "blotter" (personal history of orders and trades), and their assignments. Agents, on the other hand, produce orders automatically, without the need of human intervention, on the basis of the market conditions that they observe. Once generated, orders are sent to the Order Manager, which routes them to the appropriate order processor (in this example, the single Exchange) depending on the destination specified by the sender. Once received by the Exchange, orders are processed according to the specific order matching logic implemented (the order matching logic that we will cover in detail here is the *price-time priority* matching logic, which constitutes the foundation of the CDA) and order completion data is passed back to the Order Manager, which in turn dispatches it to the appropriate sender. It is worth noting that order data are private, as only the originator of an order receives the order completion data relative to that specific order, which will let him/her know its progress. Conversely, market data are published on the Market Data Bus and can be seen by every market participant.

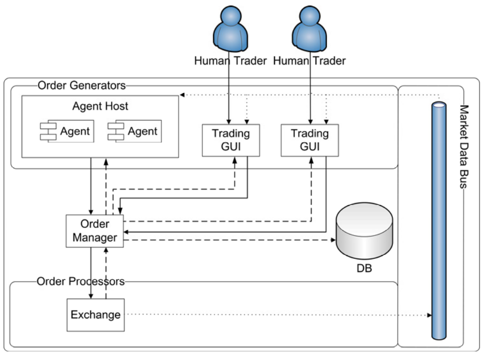

Figure 1: An instance of Open Exchange. The solid lines and the dotted lines represent the flow of order data, respectively the requests and the replies. The sparsely dotted lines indicate the market data flow, from the Exchange back to the order generators through the Market Data Bus.

4 AGENTS

In the Open Exchange framework, automated trading agents are implemented as individual plug-ins running on an instance of the *Agent Host*. In line with the distributed architecture of OpEx, there can be multiple instances of the Agent Host, each one running a particular set of Agents. Every Agent implements one specific algorithm and has its own configuration settings, loaded at start-up. One instance of the Agent Host is capable of running multiple instances of the same Agent, so that more than one automated trader following a specific strategy can participate in the market simultaneously. The behaviour of an OpEx Agent consists of cyclically listening to *stimuli* and reacting to them sequentially by performing one or more actions. Agents are idle as they wait for the next stimulus, whereas they perform calculations and they can send a signal to the market when they are active. Each stimulus represents a precise event (e.g. "the activation timer has expired", "an order has been sent", or "there has been a trade") and it is produced by a specific source asynchronously. Unprocessed stimuli are convoyed to a common collector, and then the resulting queue, sorted chronologically, is processed sequentially. Our choice of timing mechanism is consistent with the previous IBM work (Das *et al*., 2001), where similar timing rules were used to regulate the activity of the Agents. However, while the results presented in

(Das *et al*., 2001) are from experiments run using two different timer periods ("fast", 1 second; and "slow", 5 second) for the different algorithms, in our work reported here we used the same timing across all the experiments in order to simplify the comparison of the performances of the different trading agents. In particular, our Agents primary timer period is set to 1 second, equivalent to the "Fast" configuration used in (Das *et al*., 2001). On the other hand, OpEx schedules the activity of the Agents in a much more basic way when running in "Discrete Event Simulator" (DES) mode. DES simulations are turn-based (300 turns in one trading day), and at each turn only one Agent is chosen at random among the active Agents, each of which has the same probability of being selected.

4.1 ZIP

In 1996, Cliff invented the Zero-Intelligence Plus (ZIP) algorithm to investigate the minimum level of intelligence required to achieve convergence to market equilibrium price (Cliff & Bruten, 1997). ZIP has been used in several subsequent studies, e.g. (Tesauro & Das, 2001) and (Das *et al*., 2001), as a benchmark for evaluation of strategy efficiency, and it was subsequently extended to ZIP60 by Cliff (2009). Each ZIP trader agent maintains a real-valued *profit margin* and employs simple heuristic mechanisms to adjust their margin using market data. In this context, the profit margin represents the difference between the agent's limit price and the shout price, which is the price that the agent sends to the market to buy or sell the commodity. By observing market events, ZIP buyers (sellers) increase their profit margin, and therefore make cheaper bids (more expensive offers), when a trade at a lower (higher) price than their current shout price occurs. Conversely, ZIP buyers that observe an accepted offer (bid) at a price higher (lower) than the one they have put on the market move towards that price by lowering their profit margin, that is bidding (offering) a higher (lower) price. The same applies to buyers (sellers) that witness a rejected bid (offer) at a higher price than the one they are advertising. The profit-margin adaptation rule used in the ZIP algorithm to dynamically respond to the market conditions is based on the Widrow-Hoff "delta rule" with an additional noise-smoothing "momentum" term. The profit margin of the ZIP traders is adjusted by a small random quantity, proportional to the learning rate of the individual agent. Consistently with (Preist & Van Tol, 1998) and (Das *et al*., 2001), we altered the original ZIP implementation to fit in the OpEx infrastructure by introducing an "inactivity timer". The timer triggers a procedure that adjusts the shout price of the agents moving it towards the best price on the opposite side of the order book. As a result, the piece of information "nothing is happening in the market" is used by the agents as an additional pricing heuristic.

4.2 GD/GDX

In 1998 Gjerstad & Dickhaut introduced a bidding algorithm, now widely referred to as GD, centred on "belief" functions that agents form on the basis of observed market data. GD agents collect the orders (rejected shouts) and trades (accepted shouts) occurred during the last M trades, and store them in a history H. When a GD agent prices an order, from the history H it builds the belief function $f(p)$, which represents the probability that an order at price p will result in a trade. For example, the belief function for a GD buyer is:

$$f(p) = \frac{TBL(p) + AL(p)}{TBL(p) + AL(p) + RBG(p)} \quad (2)$$

Here, $TBL(p)$ represents the number of accepted bids found in H at price $\leq p$, $AL(p)$ is the number of asks in H with price $\leq p$, and $RBG(p)$ is the number of rejected bids in H at price $\geq p$. Note that $f(p)$ depends on H, and therefore it can potentially change every time a market participant sends an order to the market. Because $f(p)$ is defined only for some values of p, the function is interpolated to provide values over the domain of all the valid prices. Finally, the price p that maximises the product of the interpolated $f(p)$ and the profit function of the agent (equal to $l - p$ for buyers and $p - l$ for sellers) is chosen as the order price. The original GD algorithm was modified by Tesauro & Bredin (2002), who christened their version "GDX". GDX substantially differs from GD in that it makes use of Dynamic Programming (DP) to price orders. The pricing function takes into account both the effect of trading the current unit immediately, and the effect of trading it in the future, discounting the latter by a parameter γ. As a result, GDX agents do not just maximise the immediate profit, but instead optimise the pricing process in order to achieve overall higher returns over the entire trading period.

5 EXPERIMENTAL SETUP

All of our human vs. robot experiments involved 6 human traders and 6 robot traders, both equally split

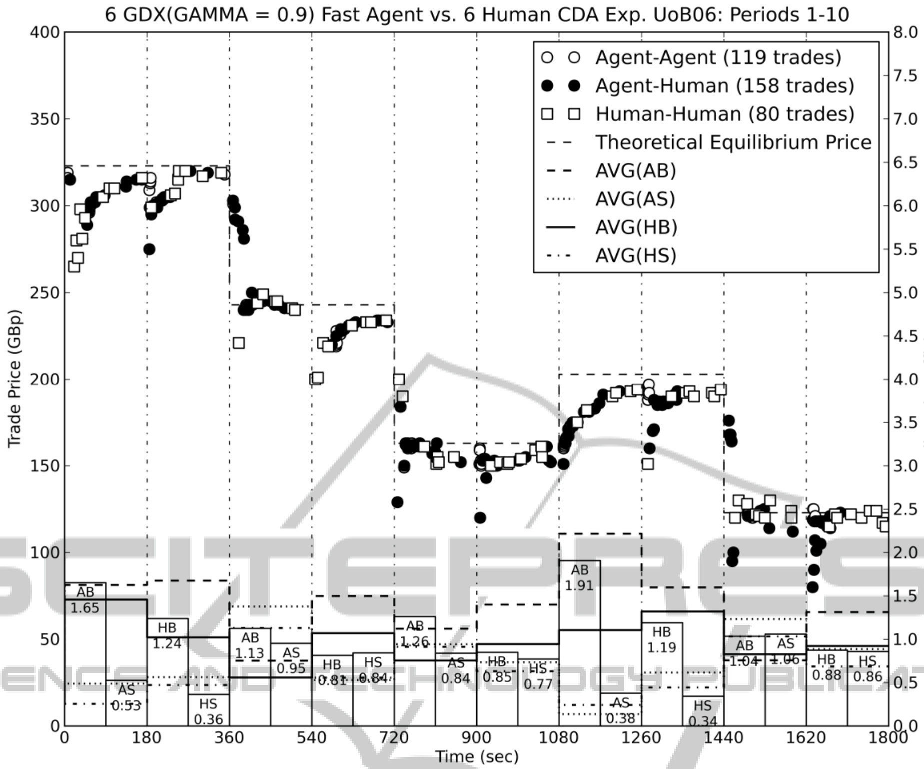

Figure 2: Trade price time series for a humans-vs.-GDX experiment. The vertical lines represent the start of a new round. The 10 rounds of 3 minutes each were divided into 5 phases, each of which with its own set of limit prices. The theoretical equilibrium price for each phase is indicated by the horizontal dashed lines. Trades between two humans are marked with open squares, between two agents with open circles, and between an agent and a human with solid circles. Mean efficiency per phase (vertical bars) and per rounds are shown for Agent Buyers (AB), Agent Sellers (AS), Human Buyers (HB) and Human Sellers (HS).

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into 3 buyers and 3 sellers, a structure used in the original IBM experiments. Before each experiment, the human subjects were briefed about the rules, and were given some time to familiarise with the Sales Trading GUI (briefing and tutorial typically took less than 30 minutes). The subjects had no previous professional experience in electronic trading, and they were only allowed to participate in one experiment. We motivated all 6 participants by giving each of them a token worth £20, plus a bonus of £40 and £20 to the first and the second best trader, respectively. An experiment consisted of 10 consecutive "rounds" 3 minutes long. At the beginning of a round, each of the 12 players received a fresh supply of 13 units to buy or to sell during that round, according to their role. At the end of the round the unused units were discarded, without any profit or loss for the traders. Players had to trade their units sequentially, and the sequence of their limit prices was arranged in an arithmetic progression. Only 3 "generator" sequences were actually used to produce the prices for all the players: a human and his/her robot counterparty had the same limit prices; and buyers and sellers share the same values except for the order, that is increasing for sellers and decreasing for buyers. The progressions had the same slope, and they were chosen so that each player had approximately the same maximum theoretical surplus in a given round. In line with (Das *et al*., 2001), we introduced market shocks by periodically altering the limit prices adding or subtracting a constant to them every 2 rounds. Thus, a 30 minutes simulation was constituted by 5 consecutive trading periods at different equilibrium prices.

6 EXPERIMENTAL RESULTS

6.1 Agents vs. Humans

The results of the four agent-human experiments, summarised in Table 1, present several significant findings, all of which are in line with (Das *et al*.,

Table 1: Summary of the four agent-human experiments. For each experiment, the table displays: the strategy employed by all six agents; the percentage of trades made between two Agents, an Agent and a Human, and two Humans; the average efficiency of Agents and Humans; the percentage difference between Agents surplus and Humans surplus; the market efficiency and the profit dispersion. The mean maximum theoretical profit per trader per simulation is 2107. Lower profit dispersion and higher mean efficiency values are better.

Experiment		Trades			Performance			Market	
ID	Strategy	A-A	A-H	H-H	Eff(A)	Eff(H)	Δ Profit (A-H)	Eff	Profit Disp
UoB01	ZIP	35%	35%	30%	1.010	0.965	5%	0.987	536
UoB04	ZIP	39%	30%	32%	1.037	0.931	11%	0.984	468
UoB05	GDX	36%	40%	24%	1.055	0.789	36%	0.923	707
UoB06	GDX	33%	44%	22%	1.074	0.809	35%	0.943	704

2001).

First, the agents as a group consistently outperformed the humans in all four experiments: the total surplus extracted from the market by the agents was on average ~22% more than the total surplus extracted by the human counterpart. Also, the efficiency achieved by the agents is constantly above 100%, which evidently implies that the agents managed to exploit human flaws.

Second, there was a substantial interaction between agents and humans: on average, ~37% of the trades happened between an agent and a human, which confirms that the humans as a group were well integrated in the mixed humans-agents market.

Third, we found that for each experiment, either all the buyers (but one) did better than all the sellers, or vice versa. Because this pattern was found neither in the numerous robot vs. robot experiments we ran under identical conditions, nor in the many human vs. human trials documented in (Smith, 1962), we speculate that this asymmetry is due to the heterogeneous nature of our market.

Finally, our analysis shows that although GDX agents as a group achieve higher values of allocative efficiency than ZIP agents when competing against humans, both the overall market efficiency and the profit dispersion values are better for ZIP.

6.1.1 GDX Agents vs. Humans

The trade price time series of the human vs. GDX experiment UoB06 is shown in Figure 2. We will refer to this specific experiment, although the observations we made on UoB05 are very similar. The dashed vertical lines separate the 10 trading periods, whereas the dashed horizontal lines mark the theoretical equilibrium price p^*. The time series exhibits a recurring pattern of convergence towards a price that is often somewhat lower than p^*. Most of the trades were made at lower prices than p^*, since buyers closed deals at reasonably lower prices than their limit prices, and therefore kept a higher profit margin than their sellers counterparty. This is confirmed by the fact that the five best traders in terms of mean allocative efficiency are buyers, for both the human vs. GDX experiments.

A more detailed analysis of the efficiency per trading period reveals that the discrepancy between buyers and sellers is accentuated by the raising of the equilibrium price (e.g. between trading periods 6 and 7), and attenuated by the drop (e.g. between trading periods 2 and 3, and 8 and 9). We explained this by looking at the first few trades made in the trading period following the market shock: their prices tend to remain close to the previous value of p^*, resulting in better opportunities for buyers or for sellers, if there was a raise or a drop of p^* respectively. This confirms that the GDX strategy requires a few samples before it can adapt to the new market condition.

6.1.2 ZIP Agents vs. Humans

Figure 3 illustrates the first four trading periods of experiment UoB04, which are quite representative for the two human vs. ZIP experiments we ran. By visual inspection, it can be verified that human-ZIP markets display better capabilities of tracking the equilibrium price, as convergence to p^* is more pronounced than in human-GDX markets. It is clear that the patterns displayed by this time series are quite different from those in Figure 2. It can be noted that, qualitatively, the shape of the time series is reasonably consistent across the trading periods, and that the curve presents a higher price excursion in a shorter time than GDX before converging to p^*. We ran a detailed quantitative analysis of the time series to confirm this, and found that the mean trade time relative to the trading period is ~45 seconds for ZIP-humans and ~69 seconds for GDX-humans markets. Moreover, by isolating the trades between two agents (A-A), between two humans (H-H), and between a human and an agent (A-H), we found that the mean trade time of the three types of trades is

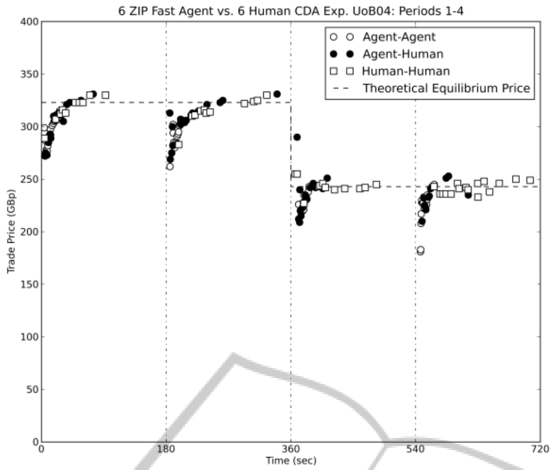

Figure 3: The first four trading periods of experiment UoB04.

Table 2: Summary of three sets of robot vs. robot experiments between GDX & ZIP agents. For each set of experiments, the table presents: the type of experiment, the value of the discount parameter γ, the number of experiments won by the two agents, and the mean number of rounds per experiments won by GDX (±1 s.d.).

Type	γ	ZIP	GDX	GDX rounds won
DES	0.0	46	1011	8.567 (± 1.817)
DES	0.9	14	985	9.094 (± 1.273)
RT	0.9	316	654	5.736 (± 1.518)

consistently higher in GDX than in ZIP. Also, the mean trade time of A-A trades is the smallest and that of H-H trades is the largest consistently across trading periods in the experiments involving ZIP, while this relationship does not hold for some trading periods of experiments UoB05 and UoB06.

6.2 Robots vs. Robots

In order to further benchmark ZIP and GDX, we ran three sets of experiments between the two agents, in a pure robot vs. robot market. The results are outlined in Table 2.

Qualitatively in line with (Tesauro & Bredin, 2002), GDX clearly outperforms ZIP in discrete event simulations, both when run in optimal mode (γ = 0.9) and when degenerated to GD (γ = 0); in particular, the performance of GDX improves slightly for γ = 0.9. However, the win-lose ratio changes radically when the experiment is run in Real-Time (RT) mode, that is using the same set-up described for human vs. robot markets. This is also confirmed by the values of the mean number of rounds won by GDX.

We speculate that the difference between the DES and the RT results is mostly due to the very nature of the two simulators: DES simulations are essentially single-threaded, and the agent selected for the current move has a virtually unlimited time to perform its calculation before ending the move. Conversely, each agent is represented by (at least) one thread in a RT simulation: agents are woken up asynchronously, therefore two or more of them may happen to operate "simultaneously" (compatibly with the software and hardware scheduling policies in force on the system running the simulation). This discrepancy is particularly relevant when comparing GDX and ZIP because the calculations performed by the latter are much more light-weighted than those performed by the former: while the GDX strategy may fare overwhelmingly better than ZIP if it is given all the required time to execute the pricing calculations, the difference between the performance of the two is dramatically reduced when time is critical, and the fastest agent to hit a price makes more profit.

7 DISCUSSION & CONCLUSIONS

We were pleased to employ our low-cost, portable experimental economics laboratory to, for the first time ever, pit humans against what is known to be the most evolved version of the "GD" class of algorithms. The results we obtained are, at the best of our knowledge, unique, and they present several noteworthy characteristics.

The application of Dynamic Programming techniques indeed proves its validity in terms of overall efficiency achieved by the agents as a group, against both human and automated rivals. The advantage of GDX over its predecessor is also confirmed by comparing our results to those realised in the IBM study, which present consistently lower values of mean efficiency of the trading agents.

On the other hand, human-ZIP markets certainly display better overall performance, in terms of market efficiency and profit dispersion. This suggests that ZIP agents would be better companions for human traders in a CDA-regulated market where the objective is to maximise the whole profit extracted, whereas GDX would be a better choice in a scenario where humans and agents are pitted against each other as two separate teams, each one trying to exploit their rivals' weaknesses to maximise their own profit.

Moreover, we note here that several features of the market dynamics observed in our experiments deserve further investigation: the curved price trajectories and their convergence to the theoretical equilibrium price; the distinct separation between buyers and sellers in terms of overall performance; and the effect of timing constraints on the algorithmic traders.

Ultimately, it would be interesting to test our algorithmic traders in two additional scenarios, compatibly with the time and money issues related to running the experiments. One where the period of the agency interventions is forced to be comparable to the estimated reaction time of the human traders: this would reveal in what measure the superiority of the agents is bound to their speed. And a second scenario where professional traders are used instead of amateurs, which would explain whether solid trading skills in the global financial markets make any difference in a competition against automated traders.

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