How multi-agent systems can be good for Behavioral Economics : a case study

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Abstract

In this work, we underline the benefit of techniques derived from distributed artificial intelligence, i.e. multi-agent systems, to the study of economical behavior. It aims to focus on the level of individual behaviors, as a bottom-up approach to understand the rise of economical phenomena like price fluctuation within a financial market or volatility within a labor market. In this paper, we propose an agent-based model of human decision making: CODAGE (Cognitive Decision AGEnt). In the CODAGE model, the decision maker is modeled by an entire multi-agent system, where each agent is in charge a particular sub-process of the whole decision. The architecture is intended to be as generic as possible. It could be viewed as an agent-based decision framework, in which different decision heuristics and biases could be implemented. We illustrate this approach with a simulation of a small experimental financial market, for which our model was able to replicate some human decision behaviors.

1 Introduction

In this work, we underline the benefit of techniques derived from distributed artificial intelligence, i.e. multi-agent systems, to the study of economical behavior. It aims to focus on the level of individual behaviors, as a bottom-up approach to understand the rise of economical phenomena like price fluctuation within a financial market or volatility within a labor market. Neoclassical economical theories, among others, favor an aggregated view: individuals are summed up into an aggregated function or a set of equations and the group is studied in place of the individual. We suggest to complement these models, or sometimes to challenge them, with a deeper study of the individual level. More precisely, for each human involved, we design an artificial (i.e. computational) cognitive agent. To do so, we derive behavioral rules from cognitive or social psychology and implement them in the way they actually reflect these psychological theories, following a methodology for cognitive design we called psychomimetism [Kant, 1999]. This belongs to the Agent-Based Computational Economics (ACE; e.g. [Tesfatsion and Judd, 2006]) approach to study economic processes modeled as dynamic systems of interacting agents.

Multi-agent systems (MAS) have been already used to model human decision making processes (e.g [Parsons and Wooldridge, 2002, Norling, 2004]), and many successful applications have been derived from these works in various fields (e.g. economics [LeBaron, 2002], electronic commerce [Guttman et al., 2002]). MAS seem appealing for human decision making because they capture the two levels of decision processes: the *individual level* (i.e. agent level), where each decision process could be modeled, from the reactive to the more cognitive one ; and the *collective level* (i.e. system level), where one has to model interactions among agents, communication between them, coordination, etc. For instance, in the field of Computational Economics, most works used rather reactive (zero-intelligence or zero-intelligence plus) agents and large-scale interactions in order to exhibit interesting market properties [LeBaron, 2002]. Other works would use more cognitive agents, mostly based on the BDI (Belief Desire Intentions) architecture [Norling, 2004].

When reactive (or zero-intelligence) agents are used, the emphasis is made on *emergence*: from a simple individual computation process, a global collective behavior emerges. This is consistent with the Artificial Life principles, stating that most of the complex phenomenon we observe in our world should be built from the bottom-up. This approach offers a variety of behaviors and phenomena at the macroscopic level. For instance, in the case of Financial Market Simulations, with few equations, reactive models could lead to equilibrium, oscillations, non equilibrium states, bubbles, that is to many phenomena observed in the real world at the macroscopic level. However, when one needs to explain these phenomena at the agent's microscopic level, the reactive approach suffers from its limitations to model the information processes the human agent may have used in the real world. In order to understand and explain complex social human functions (real markets, organization dynamics, coalition formation), more complex (i.e. more cognitive) models of human mind and actions are needed [Castelfranchi, 2001].

In the case of decision making, where can this more complex (more cognitive) theory be found ? In the last years, Classical Decision Theory and Game Theory have been used to design multi-agent systems. This includes classical (e.g. utility-based) theory models, extension of utilities, and Markovian Decision Processes (see [Parsons and Wooldridge, 2002] for a review), and yields several interesting applications. However, most of them are not compatible with the limitations of human capabilities, as stated by Simon with his concept of bounded rationality. Decision and Game Theories usually imply optimization processes, while agents are to explore a quasi-infinite (or exponential-growth) search space. And even if one relaxes this request of optimality, cognitive psychology has shown that humans violate most of the principles underlying Decision Theory Models. To understand this, let us tell a little about what cognitive psychology shown on human decision making.

2 Models of human decision-making

One can define decision-making as *the process of selecting a course of action from multiple alternatives*. According to classical decision-making, the decision-maker is said to evaluate these alternatives according to several criteria. Aggregative models decompose the decision-making process in three steps: (1) determine the utility of each alternative, (2) maybe include the uncertainty and probability informations, and (3) choose the best alternative on the basis of these utilities. However, evidence from a lot of experiments prove that the actual decisions of human are *biased*. Due to cognitive limitations, human cannot represent and evaluate all the alternatives (Simon, [Simon, 1955]). The bias and heuristics research (Kahneman, Slovic and Tversky [Kahneman et al., 1982]) has listed some heuristics used during the perception, representation and selection processes. Elimination By Aspects (Tversky & Kahneman [Tversky, 1972]), the *satisfycing* solution paradigm [Simon, 1955] or Probabilistic Mental Models [Gigerenzer and Goldstein, 1996] also explain how the alternatives can be compared with a computational model (and not an aggregative one). Other models claim that decision is essentially based on previous decisions: the decision-maker soves frequently the same problems or the same type of problem. Klein proposed a model called Recognition-Primed Decision model [Klein, 1993].

All these descriptive models focus on the selection process between several alternatives. But they explain neither how these alternatives are built nor how the environment is perceived and represented. Several authors [Simon, 1955, Brunswik, 1952] underline the relation between this decision process and the environment itself. According to this point of view, the decision making process could be defined as *the cognitive process of reaching a decision*. The first step, *perception*, is selective and imperfect. It provides raw and complex informations that cannot be used in this form. The decision-maker has to *integrate* this data, i.e. to make it into the decision-maker frame of reference. Then the alternatives are built. If the decision-maker is not given any external choice, he has to provide himself these alternatives (case of the chess player) based on personal knowledge.

However, is it relevant to see decision-making as a unique kind of process ? Prior studies show that several strategies can be used: case-based reasoning [Klein, 1993], analytical analysis and so. Classical Decision-Making distinguish the expert decision-maker (opposed to the naive decision-maker), which has accumulated knowledge about his domain and uses adapted methods for solving problems. Decision-making is also influenced by investment in a task: if the decision-maker has to find a perfect decision (expert who has to justify his choice, for instance) he will invest a lot of cognitive ressources. But if the consequences of the choice aren't risky, as for a consumer buying fruits, he will adopt a rapid and cognitively costless strategy.

ACT-R [Anderson et al., 2004] and SOAR [Laird et al., 1987] propose computational models which include memory retrieving (for building the alternatives which are studied) and choice steps. But they impose specific knowledge representation (chunks and production rules) which allow to manipulate other symbolic levels like variables. So we decide to build our own model, compliant with evidence of human decision-making processes cited before and the global scheme of Simon.

3 A generic decision architecture: CODAGE

The CODAGE (Cognitive Decision AGEnt) [Kant and Thiriot, 2006, Thiriot and Kant, 2006] model is aimed to reproduce the decision behavior for one human subject. Broadly speaking, the CODAGE agent is a *macro-agent* managed by a cognitive multi-agent architecture. The MAS comprises a set of specialized agents, we call *micro-agents* in order to distinguish them from the CODAGE macro-agent they belong to, and a tree of alternatives to facilitate information sharing, as depicted in Figure 1 below.

3.1 Knowledge representation

3.1.1 Facts

In CODAGE, we represent facts with a set of attributes, values, and predicates. For instance in a trading game, `$capital[capital_euros]=2501.2` means that the attribute "capital" has a value of 2501.2 and this numerical value is typed as "capital_euros"; `buy_proposition(alice,3,14.5)` encodes the fact that Alice proposed to buy 3 stocks at

14.5 euros each. We add two important mechanisms to encode the information processing prescribed by our cognitive model : salience and tree of alternatives.

3.1.2 Salience

The *salience*[1] of a fact represents its importance within the selective attention process. Each micro-agent ma of global agent pool $\mathcal{P}$ can vote to set the salience of a knowledge K within an alternative C (context, i.e. a possible state of the world). We denote $v_{ma,K,C} \in [0,1]$ the resulting value of such a vote. If the value is strictly positive, K is added to C with the corresponding salience value $v_{ma,K,C}$ if K is new to C ; if K is already instantiated in C, then its value is simply updated in the equation 1 that gives the final value $S_{K,C}$ of the salience of a given knowledge K within the context of an alternative C as the mean of the micro-agents ' votes:

$$S_{K,C} = \frac{\sum_{ma \in \mathcal{P}} v_{ma,K,C}}{card(\mathcal{P})} \tag{1}$$

Neurobiology supposes that a salient fact is processed more quickly than an non-salient one [H.-C., 2000]. In our model, knowledge-source agents will focus their attention on salient facts. This is implemented with two kinds of delays: an *event propagation delay* $d_{K,C}$, which causes agents to be warned later for non-salient facts, and a *reaction delay* $d_{R,C}$ for each rule R activable in a knowledge-source agent (see [Kant and Thiriot, 2006, Thiriot and Kant, 2006] for more details on delay's computation).

3.1.3 Tree of Alternatives (TA)

In CODAGE, the knowledge that the decision-maker has about the world is encoded into a decision tree[2], as the one depicted in Figure 1.

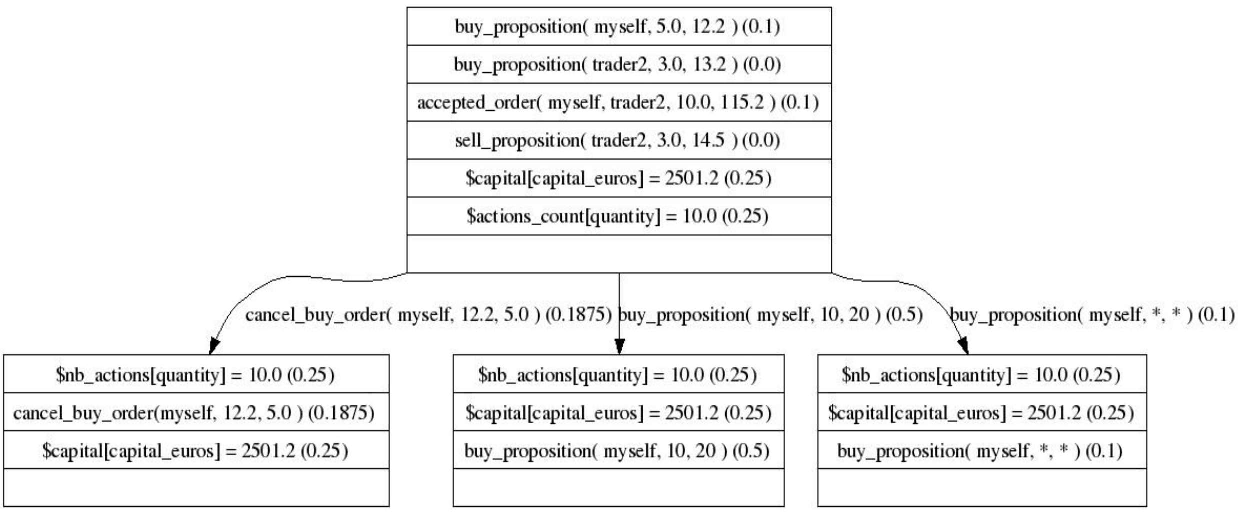

Figure 1: A Tree of Alternatives

[1]Several psychological studies support the concept of salience. Due to lack of space, we suggest this review of salience effects [Haynes and Kachelmeier, 1998]

[2]We do not assume that a human decision-maker actually has such a decision tree inside his/her head. This is just a convenient modeling tool to tackle alternatives management in our model.

Each node is an alternative that represents a possible state of the world (past, current or future). TA is a decision tree, as in decision theory, but it will be only partially built and explored to be consistent with bounded rationality. TA works at a symbolic level: each alternative represents an instantiation context in which each micro-agent may add a fact and/or an action into the tree: this is a way to share information between micro-agents. Each fact in the tree has a salience that measure its degree of importance.

Arcs between alternatives nodes represent *transitions* in time, that what produce the transition from one alternative (parent) to another one (child). We implemented two types of transitions that triggers the change to a new state of world:

- *action* transition: a possible action, performed by the macro-agent (myself)
- *fact* transition: the probability that some attribute will have a certain value (e.g. the final stock value will be 56.2 Euros at the closing of the market) or that an other agent perform some action (e.g. bob has sold 5 stocks to alice at 14.6 Euros)

3.2 Agents

Each agent encodes a subprocess of the decision system, like an heuristic, an inference mechanism, perception, etc.

The *perception agent* (abbreviated as **PER** in the remaining part of this paper) imports informations from environment: e.g. buy and sell orders, accepted transactions and so. This knowledge is introduced at the root of the TA as symbols, predicates and variables. Initial salience values are set, depending on decision maker's habits and experience (what he/she is used to consider as important information)[3].

The *egocentric agent* (**EGO**) helps the macro-agent to selectively enhance the salience on every facts and actions he/she is involved in (e.g. the orders he gave, the proposals he made).

The *world rules agent* (**WRU**) contains the knowledge about the world rules. It encodes the main rules and constraints within the environment like the possible actions (e.g. in our simulated game, a trader can emit buy or sell order, or cancel a previous order), the forbidden actions (e.g. to buy with a null capital), and some anticipated consequences of actions (e.g. if an order is accepted, capital and bids count are updated according to a particular formula).

The *expertise agent* (**EXP**) contains a set of domain-specific heuristics and strategies the decision maker may use to perform his/her actions. In our example of a trading game, these strategies will increase the salience of critical attributes like total capital, gain and loss. They will give the relevant hypothesis to explore, like buying or selling a share. They also value the different facts (e.g. in term of expected outcomes).

The *anchoring agent* (**ANC**) gives the set of anchoring values, that will be used as reference points. In a predicate where some attribute value is unknown, the anchoring agent enumerates all possible values, and will propose to anchor to an already perceived value or to a given reference-point value, e.g. a value linked to the personal situation of the decision maker, or a constant specific to the problem domain (a national interest rate for instance).

[3]In real-world applications, we could ask some experienced subjects to give their rankings importance for a set of domain facts, and derive the initial salience from this. However, when we will design a learning mechanism for the salience, the importance of these initial values will be much lowered (Cf. section **??** in the discussion)

The *uncertainty agent* (**UNC**) encodes the uncertainty of informations in the TA. It (i) sets probability p_K for a fact K to occur, and (ii) sets the probability $Pr(C)$) of alternative context C to occur in the real world.

The *decision agent* (**DEC**) monitors the decision tree and implements the search for dominance. When an alternative is added into the tree, it evaluates it. If this is a *satisficing solution*, the tree building process is stopped, and the action that created this branch is selected. If the alternative is too low (the aggregated utility of this alternative is lower than an elimination threshold), it is ignored. In other cases, the alternative is considered to be studied later, and added to an internal list. When this list is full, the alternative having the highest aggregated utility is selected. We compute the utility of an alternative A as follows :

$$AU(A) = f(\sum_{C \in Child(A)} Pr(C).u(C)) \tag{2}$$

where $Child(A)$ is a the set of immediate children of A in the tree. $Pr(C)$ the probability given by UNC agent (see above) and f is an utility normalization function, a numerical function valued in $[0, 1]$. For instance, we could adopt CARA (Constant Absolute Risk Aversion) function for risk-averse subjects $f(x) = -(1/\rho).e^{-\rho.x}$, where $\rho \in [0, 1]$ is a risking factor.

The utility $u(C)$ of an alternative C is given using a classical multi-attribute utility model, where we use the salience to weight each fact :

$$u(C) = \sum_{K \in C} p_K.S_{K,C}.v(K) \tag{3}$$

where K is a knowledge fact in C, p_K his probability, and $v(K)$ its associated value (e.g. expected outcome) as given by EXP agent. It is worth noticing this influence of salience (computed by the other agents) into the decision process : the most salient knowledge will have the highest weight in the utility function.

3.3 Decision process overview

We summarize the decision process in CODAGE with the flow charts depicted in Figure 2.

Intelligence (a) The perception agent represents the current world in the root of the tree TA. (b) As soon as information appears, the EGO agent look for personal concerns and increases the corresponding saliences. Expertise agent may also update salience based on new information and its heuristics, while ANC agent increase the saliences of anchored values.

Design (c) Based on the most salient facts, agents use the TA to simulate actions, and to anticipate events and other decision maker's actions in a short or medium term. New alternatives are added to the TA, from EXP, WRU and DEC among others.

Decision (d) In parallel with (b) and (c), the decision agent assesses alternatives (utility computation), apply dominance search that leads either to the choice of an action or a selection of alternatives to be further explored.

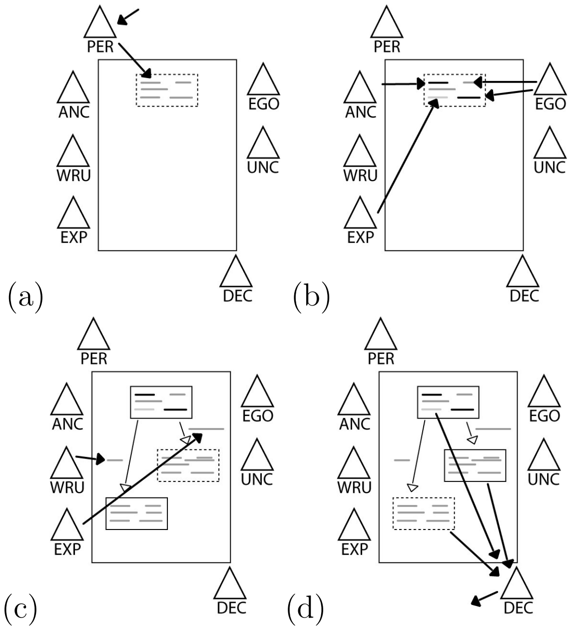

Figure 2: CODAGE decision process overview

4 Application to a financial experimental market

4.1 Description of the experimental market

The chosen experimental market is based on an article from [Biais et al., 2005], which describes an experimental financial market to analyze the discovery of equilibrium strategies and valuation in experimental financial markets with differential informations.

This market is a continous call (double-auction) market that lasts seven minutes. During that period, traders place limit orders for one share each, announcing it to the experimentator, who writes theses offers on a blackboard, which all the other traders can see. Traders can then accept these limit orders which creates a trade, and an accepted order is then written on the blackboard. At the beginning of each market, all traders receive 25000 credits and 4 shares which they can place sell limit orders on. They also receive heterogeneous private signals on the value of the shares which implements the differential information aspect. Share values can be either **490**, **240**, or **50** credits. If the dividend is 490 credits, half the traders will receive information that it is not 240 while the other half will receive information that it is not 50. The same rule applies if the value of the share is 240 or 50, although they never know the real price of the share.

Each trader can place limit orders. Limit sell orders specify the number of shares as well as the minimum price below which it is not interested to sell. Limit buy orders specify the number of shares and also the maximum price above which it is not interested to buy. In the experimental market, we use limit orders for one share only, but multiple limit orders can occur from one trader.

An accepted order, which represents a trade, is written to the blacboard when a sell limit order and a buy limit order match *(e.g : Buy Limit Order value >= Sell Limit Order value)* and are validated by the experimentator.

4.2 Instanciation of CODAGE for this experiment

We set the behavior of each micro-agents in order to comply with the experiment protocol described above. Moreover, we need to add to the EXP (expertise agent) some reasoning process, so the agent could estimate the price of the share, and use this estimation for its decision process. We designed and tested four reasoning models, with an increasing complexity :

Random price estimation model (RAND)
This was the initial step for the curve generation. The real price of the share deduced by the Expert agent is then modified to bear a benefit when posted to the continuous call market's blackboard depending on the share price being a sell or a buy proposition.

$$V = \text{share value deduced by the Expert Agent}$$

$$VSell = (1+\alpha) * V,\ \alpha \in]0,1[$$
$$VBuy = (1-\beta) * V,\ \beta \in]0,1[$$

The $VSell$ value describes the behavior of a Trader posting a buy proposition and trying to make a profit by raising the estimated price of the share, and vice-versa for the $VBuy$ value.

Average share price model (AVE)
This model was used to smooth the incoherent oscillations brought by the **RAND** model. It should produce smoother curves and closer to the Biais et al. experimental market curves, in which we observe variations during the start of the call auction then a stabilisation towards the estimated share values.

$$VSellEstim = \frac{\sum_{i=1}^{N_a} sellLimitOrders_i}{N_a}$$
$$N_a = \text{number of sell limit orders}$$

$$VSell = V + (\alpha * (VSellEstim - V)), \alpha \in]0,1[$$

$$VBuyEstim = \frac{\sum_{i=1}^{N_b} buyLimitOrders_i}{N_b}$$
$$N_b = \text{number of buy limit orders}$$

$$VBuy = V - (\beta * (VBuyEstim - V)), \beta \in]0,1[$$

If there are no buy limit orders or sell limit orders available, the **RAND** model is used.

Average share price on the orders model (AOE)
This model is the first to introduce the exchanges between CODAGE agents, and helps the selling or buying behavior of the agents to converge towards the value of previous trades between agents.

$$VAccSellEstim = \frac{\sum_{i=1}^{N_a} accSellLimitOrders_i}{N_a}$$
$$N_a = \text{number of accepted sell limit orders}$$

$$VSell = V + (\alpha * (VAccSellEstim - V)), \alpha \in]0, 1[$$

$$VAccBuyEstim = \frac{\sum_{i=1}^{N_b} accBuyLimitOrders_i}{N_b}$$
$$N_b = \text{number of accepted buy limit orders}$$

$$VBuy = V - (\beta * (VBuyEstim - V)), \beta \in]0, 1[$$

During the initial phase of the market, when there are no accepted buy or sell orders, a modified **AVE** model is used. The modified model generates random sell or buy orders at the price deduced by the CODAGE agent, without profit, which will tempt the other agents to trade. Its purpose is to enable the use of the **AOE** model with initial accepted buy and sell values.

Global average share price on all orders with random irrational behavior(AOES)

This is the last model used in the decision process of the CODAGE agent. It is a combination of the **AOE** and **AVE** models along with the use of a random irrational behavior. In this model, we consider all the accepted orders, but also the buy and sell limit orders. We compute the average of the results of the **AOE** and **AVE** models, and use this value for the final price proposals for the next buy and sell limit orders.

$$VSellAvg = \frac{VAccSellEstim + VSellEstim}{2}$$

$$VSell = V + (\alpha * (VSellAvg - V)), \alpha \in]0, 1[$$

$$VBuyAvg = \frac{VAccBuyEstim + VBuyEstim}{2}$$

$$VBuy = V - (\beta * (VBuyAvg - V)), \beta \in]0, 1[$$

We also add an irrational behavior which is similar to the random sell or buy order emissions from the **AOE** model but closer to the observed irrational behaviors. When the final price proposal is between 90% and 110% of the real value of the share, there is a 0.15 probability that the agent will act irrationally and propose a share or a buy with the real value of the share.
This model provides a good approximation of the traders' behaviors observed during the Biais et al. experimental market, where we consider that both the accepted order values and limit order values are important in order to estimate new share values, along with random occuring irrational behaviors observed during the experimental market.

5 Results

In order to validate the CODAGE model, we ran a series of tests using the diferent reasoning models aforementioned and checked them against one of to one of the curves from Biais et al's experimental market, which gives a significative pattern of behavior from the test subjects during the double auction market. We tried to approach the curve by gradually using more refined reasoning models to the agents as stated previously.

All the test runs were done considering only the continuous market, whereas the market curves of the experimental market are spanned over the preopening, call and continuous market. Nevertheless this gives a good comparison for validating the agents' behaviors and provides opportunity for further testing and reasoning models.

As Biais et al.'s experimental market used only one share value (**240**), all the runs used that value as the true share price. Also, all the CODAGE agents are considered to be using explicit incentives as they try to maximise the profit obtained from share trades.

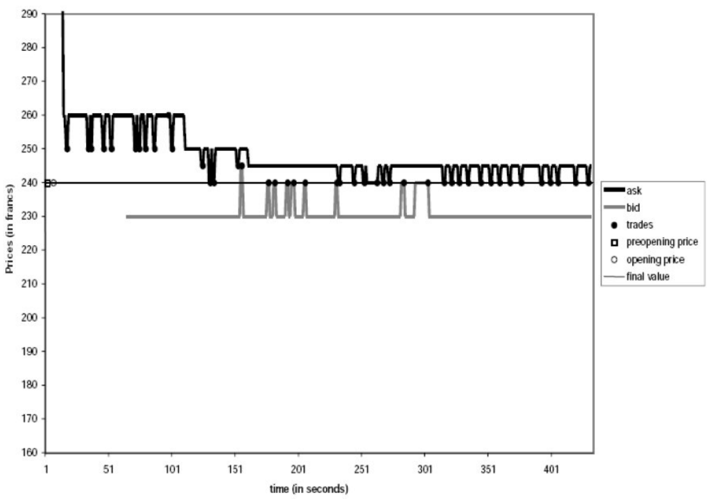

Figure 3: The experimental market curves used as a reference

Figure 3 displays the behaviors of the human subject in the experiment. The upper blodface curve displays the asks, while the lower displays the bids. These market curves show a convergence of the buying and selling prices towards the real value of the share, with most trades occuring at the true share price during the continuous market.

In the following subsections we will be provinding significative result curves from the test runs and analyse them from the point of view of the reasoning models.The green curves represent the occurence of sell limit orders, and the red ones the buy limit orders.

5.1 The RAND model

The results for the RAND model are depicted in Figure 4. This model provides another way of validating the CODAGE decision process where we observe buy and sell limit orders posted on the market, according to the estimated true price of the share. The importance of the reasoning models is not taken into account yet, so the results differ from the experimental ones.

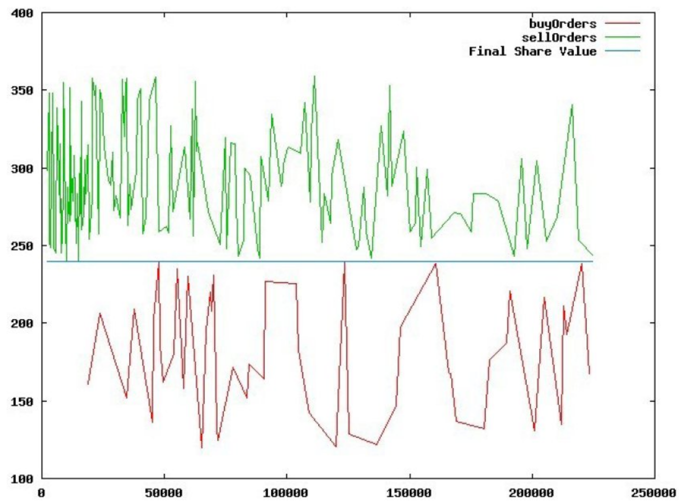

Figure 4: Result curves for the RAND model

5.2 The AVE model

In the curves obtained from the AVE model (see Figure 5), we notice an important change compared to the results from the RAND model. The buy and sell limit orders are now closer to the expected real value of the share after a number of steps, exploiting the average value of previous offers in the majority of the test runs. The price oscillations between share values obtained from random share prices are reduced, due to the calculated distance between the estimated values and the read values added to the estimated real value. Of course, the average value depends on the first values generated from the RAND model and gets closer or farther to the expected real value depending on these generated numbers.

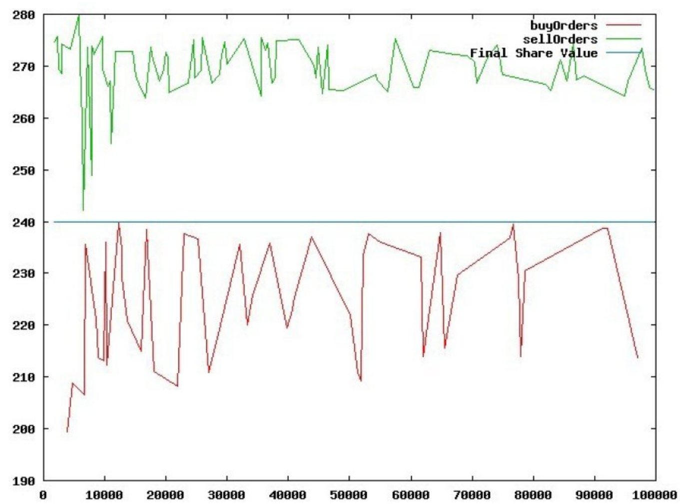

Figure 5: Results for the AVE model

5.3 The AOE model

In the AOE model (see Figure 6), we no longer focus on the buy and sell limit orders, but we estimate prices on the accepted buy and sell limit orders (which resulted in a trade). This causes a very quick convergence towards the estimated real share value after the use of the RAND model for the first limit orders, following which the agents proposing sell limit orders stagnate at the estimated real share value. The behavior was not observed for the agents offering buy limit orders, which is unexpected and needs further investigation.

This model provided ways of approaching the irrational behaviors of proposing limit orders without profit, and observing trades between agents at the estimated real share value.

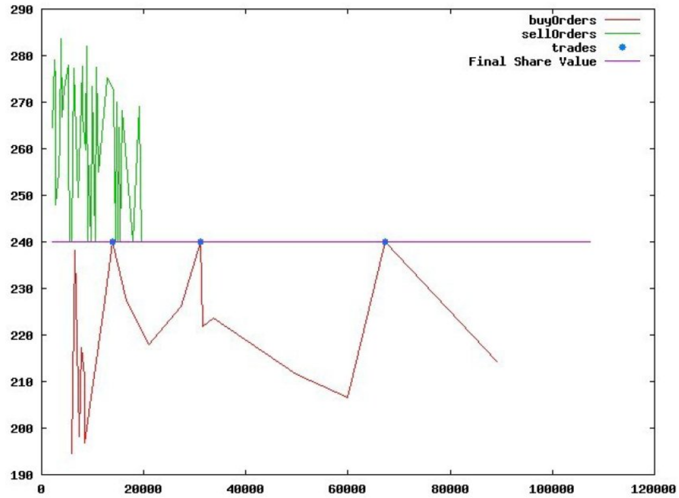

Figure 6: Results for the AOE model

5.4 The AOES model

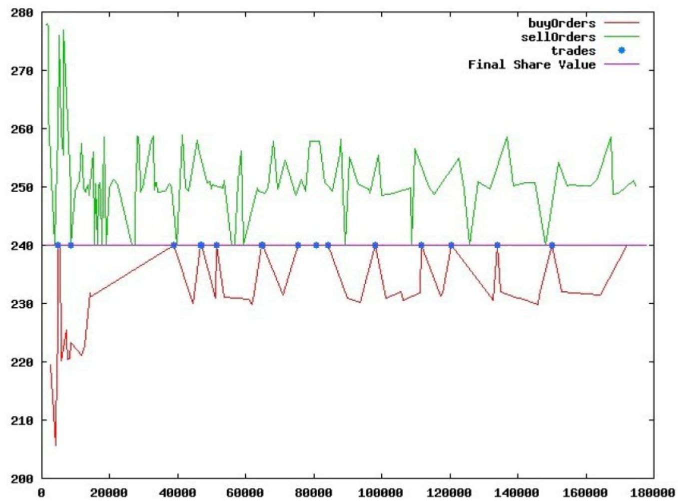

Figure 7: Results for the AOES model

Finally, as shown in Figure 7, the AOES model is the last proposed to approach the experimental market's behavior, and the one which is the closest to the expected market behavior. Using the information of both proposed and accepted limit orders, the generated buy and sell limit orders are much closer to the experimental market's curves and provide a satisfactory agent behavior as a trader for the requirements of the experimental market. This model is the one that takes advantage of most of the information available from the experimental market, where the agents use the concept of memory to recall the previous values of limit orders and accepted orders and propose their own orders according to market trend and search of profit, which is what a trading agent would be expected to do.

6 Discussion

In this paper, we have described a generic agent-based decision model, CODAGE, and show how it could be use to reproduce an experimental financial market. The peculiarity of CODAGE is that it views the human decision making as a multi-agent systems, and the decision emerges from the interaction of several specialized micro-agents.

Thanks to our cognitive and agent-based methodology, we have designed several reasoning models, with a cognitive increasing complexity, and proposed them to take the experimental data into account. The AOES model, that makes the best use of available information, was the best fit for these data. This finding might challenge the idea that Zero-Intelligence traders [Gode and Sunder, 1993] (the RAND model in this work) are enough to cope with financial decision data: in the experiment we studied, this is clearly not the case.

We now conclude this paper with some possible improvements of this work, for the experimental market simulation and for the CODAGE model itself.

6.1 The experimental market

We have laid the basis for the experimental market and observe that a CODAGE agent possesses the necessary cognitive processes to show a proper behavior in a trading market environment. The test runs still need further improvement, such as decomposing the different phases of the experimental market (pre-opening, auction call and continuous) rather than focusing only on the continuous call. Interestingly the first generated orders provided by the RAND model in the early stages seem to fit well in the pre-opening phase of the experimental market where prices are discovered and adjusted, so providing a proper reasoning model for each phase could provide even closer results towards the market curves proposed in Biais et al.

There are also possibilities for even further improvement of the AOES model, for example in trades occuring at prices different to the expected real share value.

6.2 CODAGE

As for the CODAGE agent model itself, there are a lot of possibilities that can be added to its cognitive features.

First, its structure enables a painless addition or removal of micro-agents that can be tailored to fit a specific cognitive model. For example, one could think of emotional agents that contribute to bounded rationality in stressful environments. Learning features, such as reinforcement learning, is one of the considered extensions of the CODAGE agent, which could enable adaptation to a specific environment through the perception of the CODAGE agent.

In its current implementation, the CODAGE agent is specific to the experimental market of Biais et al. It should provide a generic operational layer independently of specific environment and semantics where the agents would focus only on modifying the tree of alternatives. The environment specific informations and interpretation could then be accessed through a second layer more specific to the problem domain, using a database exploitable by the CODAGE micro agents. This would enable easier implementation of CODAGE agents using factorisation.

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