OVERHEARING IN FINANCIAL MARKETS
A Multi-agent Approach

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Abstract: Open complex systems as financial markets evolve in a highly dynamic and uncertain environment. They are often subject to significant fluctuations due to unanticipated behaviours and information. Modelling and simulating these systems by means of agent systems, i.e., through artificial markets is a valuable approach. In this article, we present our model of asynchronous artificial market consisting of a set of adaptive and heterogeneous agents in interaction. These agents represent the various market participants (investors and institutions). Investor Agents have advanced mental models for ordinary investors which do not relay on fundamental or technical analysis methods. On one hand, these models are based on the risk tolerance and on the other hand on the information gathered by the agents. This information results from overhearing influential investors in the market or the order books. We model the system through investor agents using learning classifier systems as reasoning models. As a result, our artificial market allows the study of overhearing impacts on the market. We also present the experimental evaluation results of our model.

1 INTRODUCTION

In finance, many researchers have developed models that capture the dynamics observed in actual markets. The models proposed for over a hundred years ago are, mostly "group-based". A group-based model (Derveeuw, 2008) describes the mass laws in a population by making very simplistic assumptions based for example on an average behaviour. For instance, modern portfolio theory (Markowitz, 1952) is based on the assumption that all investors are similar in their attitude to risk. Thus conventional finance studies trader populations whose aggregated behaviour is described by globalizing mathematical equations systems. But this theory does not reproduce stock prices data series properties. Because of these limitations, some researchers have turned to individual-based models (Derveeuw, 2008). These latter models put system actors at the heart of the model. Each part is modelled individually together with its relationships with other entities. Multi-agent systems (MAS) are part of individual-based modelling. In these models, agent behaviour is a consequence of its observations, knowledge and interactions with other agents. The individual-based approach fully meets requirements imposed by complex systems studies as financial markets. Multi-agent modelling and simulation of

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markets can seize the complexity without reducing it. Despite the existence of multi-agent financial markets models as the SF-ASM (LeBaron, 1999) and the extended Genoa Artificial Stock Market (Cincotti, 2006), informal interactions between investor agents have been neglected, hence our focus on overhearing concept to address these problems.

In MAS, the communication is generally organized in protocols determining the order of exchanged messages. This limits the impact of communication, and in a highly interactional, as financial markets, this is insufficient since the interactions are not only based on pre-established protocols, but also on the need that each agent has to interact in its environment. In (Dugdale, 2000) where the objective is to simulate the interactions in an emergency call center, it is shown that overhearing (Balbo, 2004) is an important factor for the effectiveness of the company agents (operators) as it directly affects their behaviour. Overhearing corresponds to the fact that an agent has a tendency to intercept messages that are not clearly directed to it. What is important is that the sender knows that this will happen. The overhearers keep within legal status, i.e. it is part of the operating system (Legras, 2003). In this paper we propose a financial market multi-agent model and introduce the overhearing concept to test its impact on it. To model the agent we use a learning classifier model. In our work, the classifiers allow on one side the representation of complex behaviours of agents based on rules and on the other side the modelling of key features that must have an investor agent which are evolution and adaptation to dynamic environment. This article is organized as follows. In Section 2 we introduce artificial financial markets. In section 3 we discuss the main existing works and their limitations. Section 4 is devoted to our model and Section 5 to the presentation of simulation results.

2 ARTIFICIAL STOCK MARKETS

While financial markets are organized in different ways, three major components emerge (Figure 1):

1. Market structure: market is structured around a set of rules describing and governing its trading details as the process of price computation. This set of rules is called market microstructure.

2. Economic agents: who invest their capitals. Around these investors, other agents exist such as brokers which may be in the market or outside.

3. Information: Investor agents make decisions using the information from the external world, information from the endogenous market itself and information from their peers.

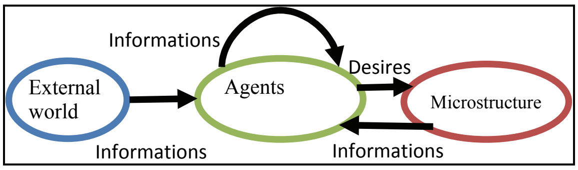

Figure 1: Market model structure.

Price fixing and market microstructure is the heart of an artificial market. Two types of microstructures exist: synchronous models need to receive the wishes of the agents before producing a price and asynchronous models that do not have time constraints. Investor agents are the most important components of the market, they continually seek their interests. To build their investment strategies they begin by assessing stocks by technical, fundamental or quantitative analyses.

Fundamental analysis is based not on the prices but on the economic reality of the business. The future asset price is based on market shares, revenues, etc.

Technical analysis provides market future trend by observation of past prices graphically or statistically.

Quantitative analysis focuses on risk of a financial asset. Whatever its origin (economic, financial), risk is reflected in fluctuation of the financial value of an asset. It is the same as the price volatility of the asset which is measured through the standard deviation of past prices. It is then interpreted as a measure of the dispersion around the average price. According to (Streichert, 2006), volatility is calculated as follows:

$$\mathrm{D(x)} = \frac{\sigma(\mathrm{x})}{\bar{\mathrm{x}}} \tag{1}$$

Where $\sigma(\mathrm{X}) = \sqrt{\mathrm{V(X)}}$ With: $V(X) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})^2}{n}$ and $\bar{x} = \frac{\sum_{i=1}^{n} x_i}{n}$. Xi is the asset X price at time i.

The more the volatility is high, the more the risk is high. This means that its price fluctuates abruptly from the highest to lowest.

3 RELATED WORK

The Santa Fe Artificial Stock Market (SF-ASM) (LeBaron, 1999) is the first agent-based artificial financial market. This model is based on the synchronization of decisions. From an equation that centralizes agent decisions through the opposition of supply and demand, new asset price is calculated. Then comes the clearing phase to make transactions between buyers and sellers agents. It is clear that this model does not reflect the transactions in a real market where each agent is free to express its desires freely. Other models such as the Genoa Artificial Stock Market (Cincotti, 2006), $-game (Andersen, 2003) or Toy Model (Bak, 1996) are synchronous in their majority, or even in the few attempts to asynchronous markets such as Toy model they lack realism considerably. For example, in the Toy Model agents can hold at most one asset. They are therefore not free to sell or buy the quantities they want to trade. This model is toy in the sense that no real market works in that way. The synchronous model is representative of the financial markets with market makers and cannot be extended to an order-driven market where transactions are done asynchronously and where the price follows the dynamics of market participants. The manner in which agents state their wishes in these models is not realistic. In most models (Derveeuw, 2008), agents make their desires in the form of a simple direction (buy or sell), while in reality they are expressed with a triplet (direction, price, quantity). Note also the existence of works in financial markets modelling such as in (Streichert, 2006), which focused on the study of time series of financial indices using the classifier Systems, but the limit is found in the neglect of the formal or informal interactions between agents in the market. Another aspect not approached in these works is the study of agents reasoning modes and therefore their behaviour evolution. In our model, we seek to emulate as closely as possible the economic reality. We use a multi-asset model. Each order is thus expanded to a quartet (asset, direction, price, quantity). The behaviours of our investor agents are complex and heterogeneous to be able to analyze and interpret the results of their behaviour. Within the same market, we model agents tolerant or risk averse, leader and follower agents. These last two types of agents are based on the overhearing mechanism.

Leader agent tries to manipulate the market taking advantage of the naivety of the other agents (followers) supposed less informed than him to make profits from future price fluctuations. Leader agent has the advantage of receiving informational signals before the others.

4 MULTI-AGENT MARKET MODEL

Our artificial financial market model (Figure 2) has three main components, namely: the microstructure of the market, agents which compose it and the external world. Our model is governed by asynchronous orders. It allows agents to make their decisions and actions autonomously. This configuration is representative of the largest financial markets like NYSE or Euronext. Modelling with order book is more complex than a synchronous market (as with Market Maker). For each asset are associated two order books (buy, sell), each containing the five best orders. The agents of the system are the market itself which manages real-time transactions and thousands of investors. An investor chooses shares to buy or sell, contacts the market and manages its financial portfolio. An investor may use the services of an Overhearing Agent which will get some information from other investor agents by using overhearing concept.

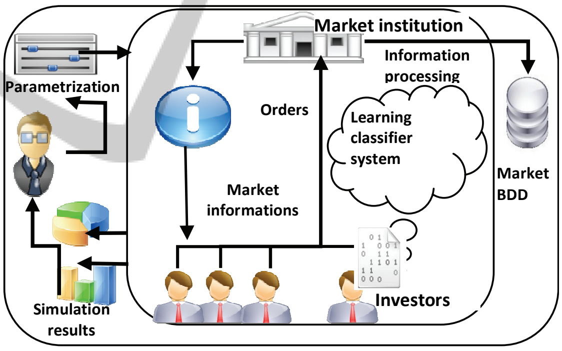

Figure 2: General representation of the system.

1. A **Market Agent (MA):** represents the financial market and has five tasks: (1) Receive orders issued by investor agents; (2) Sort orders by their types, directions and arrival times; (3) Asset pricing; (4) Communicate order books to investors; (5) Check the satisfiability of orders, conduct transactions and ensure payment.

When the Market Agent finds two orders of opposite directions that are counterpart, it makes the transaction after confirmation from both parties. Therefore, the market agent saves the transaction and updates the concerned orders then informs the two investor agents that the transaction was made.

2. **Overhearing Agents (OA):** provide information not displayed on order book to investor agents having request it. They perform the following tasks: (1) Follow buying and selling orders of the investors

that it is responsible to overhear; (2) Sort information gathered for each asset and communicate it to investors asking overhearing. Overhearing Agent represent the concept of overhearing in our system. These agents will "hear", which means intercept messages from an agent or a group of Investor agents when they receive the request from one or more agents. The main function of Overhearing Agent is to sort the information it has collected and distribute to requesters (Figure 3).

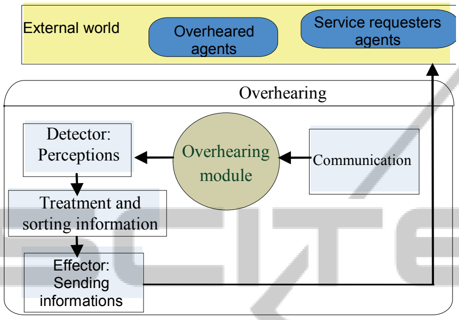

Figure 3: Overhearing Agent internal architecture.

Overhearing Agent shall first make a classification of agents according to their portfolio amounts. The first agents in the ranking will be overheard. Overhearing Agent intercepts all transaction confirmation messages issued by these agents and sends the results to the requester (Figure 4).

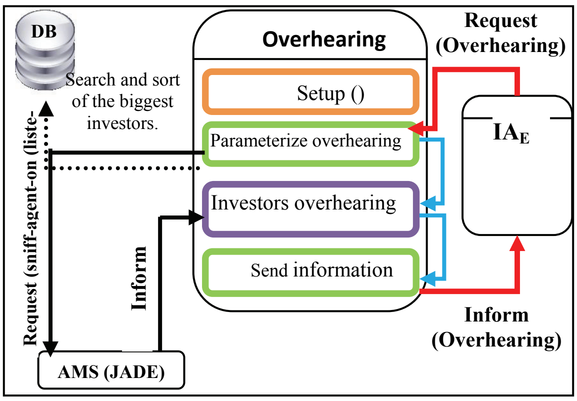

Figure 4: Overhearing process stages.

Investor Agents are constantly interacting with the Market Agent by sending orders and with the Overhearing Agents through their possible requests for overhearing.

3. **Investor Agents (AI):** influence stock prices. An Investor Agent performs the following tasks: (1) Issues an order on an asset; (2) Consults order books to be informed by the other agents desires; (3) Consults and manages financial portfolios; (4) Uses Overhearing Agent services; (5) Makes payment if the agent is buyer or increases its liquidity if seller.

We distinguish two types of Investor Agents: IAE asking the services of an Overhearing Agent and IA without access to this service. To achieve its goals, Investor Agent may make a request to overhear to an Overhearing Agent. The latter will then overhear other Investor Agents and gather information concerning their transactions and the amount of their portfolios. It also classifies the overheard agents by the amount of their portfolios and then informs the Investor Agent. An Investor Agent's primary goal is to be always satisfied or win whatever the transaction. To achieve this, it will be equipped with a reasoning module allowing it to adapt to its environment and to learn from past experiences (bounded rationality) (Kotzé, 2005). Learning Classifier systems (Arthur, 1994) are the support we used to model such agents (Figure 5). Investor Agents ***IA*** use order books available assets on the market to make decisions while the $\boldsymbol{IA_E}$ is driven by information obtained by Overhearing Agents. These agents intercept messages of overheard Agents and transmit them analyzed to Investor Agents.

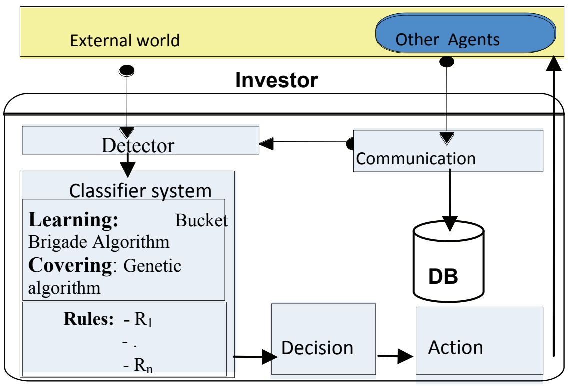

Figure 5: Internal architecture of the Investor Agent.

To approach the reality, we introduce two pairs of behaviours to the two categories of Investor agents:

1. ***(Risk Tolerance, Risk Aversion)***: an Investor Agent may be either risk-averse or risk-tolerant. In the first case, Investor Agent wishes always to be sure that the transaction is with no risk. The risk tolerance ***TR***, is then equal to 0 throughout the simulation.

In the second case, the agent will have a certain percentage of risk tolerance, the variable ***TR*** is equal for example to 20%, and this means that the agent will choose an asset with risk which may not exceed 20%. For risk-tolerant Investor Agents, the ***TR*** variable is not fixed; it will be updated according to their portfolios changes.

2. ***(Leader, Follower)*:** other behaviours that we consider are follower or leader feature of an agent. An Investor Agent Leader will not be influenced by the actions of other Investor agents, therefore it will not use the services of an Overhearing Agent. If Follower, its decisions will be governed by the actions of other Investor agents; it is this class of agents who use the services of an Overhearing Agent. This behaviour enables Investor Agents to make decisions in the form of the following quadruplet: ***(asset, direction, price, quantity)***. Let's see how the quad is generated.

5 INVESTOR AGENT REASONING

We note the choice of asset and direction (buy or sell) is the first step in decision making for an Investor Agent. This selection is done through the classifier system of each class of agent (IA_E and IA). The price is calculated by agent according to its nature and tolerance or aversion to risk (Table 1).

Table 1: Summary of the pricing policy.

F/L	IA_E/IA	A/T	Pricing policy
0	0	0	Agent follows overheard agent price.
0	0	1	Agent follows the price of the overheard agent and adds the percentage of risk tolerance.
0	1	0	Agent takes the first price in the order book which ensures the transaction (a counterpart).
0	1	1	Agent randomly chooses a price in the order book
1	1	0	Agent randomly chooses a price in order book and adds or subtracts it 2%.
1	1	1	Agent randomly chooses a price in the order book and adds or subtracts it 5%.

F: Follower agent (0); **A**: Risk-averse (0);
L: Leader agent (1); **T**: Risk-tolerant (1);
IA_E: Investor Agent using overhearing agent services (0);
IA: Investor Agent not using overhearing agent services (1);

The quantity is the last variable to be determined in order to complete the quadruplet and issue an order to the market agent. The quantity is calculated as follows: when the Investor Agent defines its asset price, it calculates the number of shares they can buy or sell by dividing its cash on price. The quantity is for example a percentage of 5% of the result.

Although they come together on how to interact with the market agent, the IAE and AI agents have two different reasoning modes through their two classifier systems CS1 and CS2 respectively.

Classifier systems allow for incrementally learn the rules that define the behaviours of the agent. To model these agents we have used the Michigan classifier system (Buche, 2006) perfectly suited to our problem since our Investor Agents must learn quickly and adapt instantly to changing situations over time. The rules of a classifier system are renewed by a genetic algorithm and reinforced by the Bucket Brigade Algorithm (Holland, 1982).

We present for each category of Investor Agent (the IA and IA_E) its learning module. We model two classifier systems, one for each type of Investor Agent. In our model, we assume that we have:

1. A number N of assets available on the market;
2. A number M of Investor Agents in the simulation. Agent behaviour will be of two types: leaders or followers in addition to their degree of risk aversion;
3. Buying and selling trends of the N assets is analyzed from order Book information.
4. At the beginning of each simulation, the user chooses the number of Investor Agents the Overhearing Agent will overhear; this number is set throughout a simulation. S is the number of overheard Investor Agents, $1 \leq S \leq M-1$.
5. To study the overhearing impact on Investor Agents and the market, Investor agents will be split into two groups; Those agents which will use the service of an Overhearing Agent and Agents which do not use this service.

5.1 Classifier System 1 (CS1)

CS1 defines asset to choose and its direction (buy, sell). CS1 corresponds to ***IA*** agents' category.

C***ondition Part*:** composed of N bits. The first bit corresponds to the first asset and the Nth bit corresponds to the Nth asset. The presence of 1 in a bit of position ***i*** means that the asset ***i*** is in buy tendency else sell tendency. When trend for buying an asset is equal to selling; this bit is set to 1, favoring purchase to sale.

***Action Part*:** is composed of $\log_2 N + 2$ bits. It indicates the asset and its direction. For a number N of assets, we need $\log_2 N$ bits to represent the asset number; we use for that the $\log_2 N$ first bits. The next bit determines if the Investor Agent will issue an order for the asset chosen or not. It is the bit of action/inaction. If it is 0 then the Investor Agent shall make no action concerning the chosen asset, if 1 then it will initiate action represented by the last bit; if the latter is 1 then the Investor Agent issues a buy order otherwise a sell order.

Reward and Selection of Best Rules: Rules are remunerated primarily depending on the type of the Investor Agent (Follower or Leader); a rule which has the purchase of an asset when there is a tendency for sale for an Investor Agent Follower, will obviously be poorly remunerated. The rules containing logical errors, such as the presence of two 1 in the last two bits of the action part will be automatically rejected. The reward is updated continuously according to the degree of agent risk aversion. For each rule the risk for the selected asset may be calculated in order to reward the rule. Note that the reward is a real number between 0 and 1. To calculate the asset risk we first compute the variance the last 10 days prices then standard deviation and finally we measure volatility corresponding to asset risk using dispersion coefficient with equation (1). The dispersion coefficient represents the risk of the asset is a percentage included in the interval [0, 1]. The more it approaches 1 the more a stock is risky and vice versa. Finally, calculation of the reward will be different depending on whether the investor agent is risk-averse or tolerate a certain percentage of risk. For risk averse investor agents the reward is calculated as in equation (2):

$$\text{Reward} = 1 - \text{Risk} \tag{2}$$

More the asset risk increases more the reward of the rule decreases. For agents tolerant to a certain risk percentage (TR), the reward is equal to (3):

$$\text{Reward} = 1 - (\text{TR} - \text{Risk}) \tag{3}$$

More the asset risk approximates to the risk tolerance TR of an agent, more the reward of the rule is well remunerated and vice versa. Note that if the risk exceeds the tolerance for risk, the reward of the rule will be equal to 0. For risk-tolerant agents, TR changes value depending on whether they win or lose money. More an agent earns, more is more its risk-tolerant, more TR increases and vice versa.

5.2 Classifier System 2 (CS2)

CS2 defines (for IA_E Followers) which Investor Agent to follow. After selecting the Investor Agent to follow, classifier system chose asset and action to perform. Followed Investor Agent is IA_E or IA.

Condition Part: It is composed of $\log_2 S + \log_2 N + 1$ bits. The first part of the condition represents the number of overheard Investor Agents. It concerns the $\log_2 S$ first bits. The second part of the condition represents the number of assets purchased or sold by the overheard Investor Agent, we must have $\log_2 N$ bits for representing all assets. The last condition bit represents the action made by the overheard agent on the given asset. If this bit is equal to 1 then Investor Agent bought this asset else it sold it.

Action Part: composed of one bit, if this bit is 1then the IA_E follow of the overheard agent else no.

Reward and Selection of Best Rules: The rules remuneration is done using three criteria:

1. Weight of each overheard agent is calculated from the amount of its portfolio, i.e., amount of its liquidity plus average values of its assets (Table 2).

Table 2: Investor agents weights to overhear (example).

N° Investor Agent	Portefolio amount	Weight
06	50.000	**0.5**
20	30.000	**0.3**
11	20.000	**0.2**

2. The risk in the purchase or sale of the chosen asset which is calculated on the price volatility during 10 days (like for SC1).
3. The risk aversion of the IA_E.

For CS2 rules remuneration, Overhearing Agent performs a ranking of the S overheard agents and calculates the weight of each one (table 2). In parallel, asset risk in each rule is calculated, as for CS1. In the end we have for each rule two values to take into account for its remuneration, the weight of the overheard Investor Agent and the risk of selected asset. These two parameters will be combined with the level of risk tolerance (TR) of the IA_E.

$$\text{TR} = 1 - \text{Risk} \tag{4}$$

The reward, as for CS1, is calculated differently according to IA_E does not tolerate any risk or when it tolerates a certain percentage of risk. For IA_E risk averse, the reward is calculated as in (5):

$$\text{Reward} = 1 - \left(\frac{\text{R} + (1 - \text{Pi})}{2}\right) \tag{5}$$

With Pi the weight of overheard Investor Agent. For IA_E risk tolerant the reward is calculated as (6):

$$\text{Reward} = 1 - \left(\frac{(\text{TR} - \text{R}) + (1 - \text{Pi})}{2}\right) \tag{6}$$

Both (5) and (6) reveal the follower nature of IA_E by introducing weight (Pi) of overheard Agents. More Agent Investor heard is classified, its weight increases more and more, and the reward of the rule which tells us to follow it will increase. For IA_E risk averse, the formula shows that more the risk is increasing more the reward diminishes and the rule is poorly remunerated. For IA_E risk tolerant, the reward increases as the risk approaches the risk tolerance. However, if the risk is greater than the risk tolerance then the reward will be equal to 0. CS1 and CS2 choose asset and direction based on two information sources. CS1 is based on order books while CS2 on overhearing the other agents.

6 SIMULATION RESULTS

Our system has been implemented in Java with JADE as multi-agent platform and Oracle 10g as DBMS. The classifiers have been programmed on the basis of ART library. JADE incorporates “Sniffer” agent to intercept agents’ behaviours. Overhearing process is derived from the Sniffer. As the Sniffer agent, an Overhearing Agent knows all the agents and when they are created or deleted.

Time management (asynchronism of our system) has been implemented at the beginning of simulation with “*Wait”* instruction for a random period for each investor agent then the sending of purchase or sale orders through a specific JADE *tickerbehaviour*.

The market agent receives investor agents’ orders through a *cyclicbehaviour*. The simulation begins with the introduction of assets, the degree of risk tolerance, the number of each type of investor agents, the number of agents to overhear as well as the number of Overhearing Agents. Simulation process start and purchase and sale transactions are displayed by asset (Figure 6). Simulation is conducted on 4 assets (Asset1 until Asset4), 3 Overhearing Agents and 20 investor agents.

We realize our simulations with two different configurations. The first one is executed with 10 AI and 10 AI_E agents. The second one with 20 AI agents (without overhearing). By the choice of these two configurations we can observe the impact of overhearing on the global evolution of the market.

We notice in the model with overhearing that the majority of agents are trading the same asset (Asset 4 in our simulation: Figure 7). It is not the same case in the model without overhearing where agents are trading in all the assets (Figure 8). We conclude that overhearing create a disequilibria in the market.

The simulation allowed us to assess the agents’ activity degree by comparing their transactions. In Table 3 we find that the agents based on overhearing are less active than the others. It’s explained by the several constraints involved in their decisions (match desires with the trend, risk tolerance, etc.).

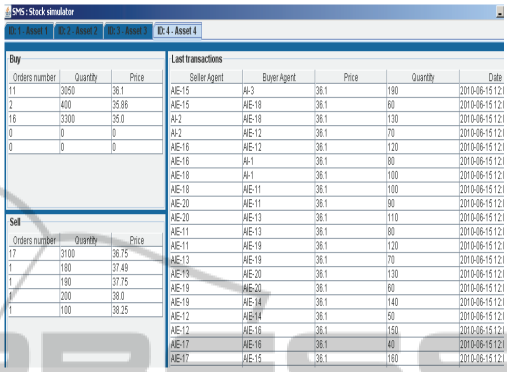

Figure 6: Simulation tracking Interface.

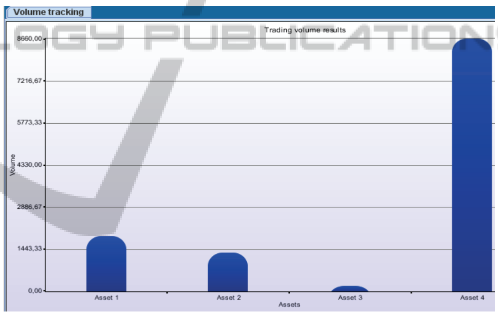

Figure 7: 4 assets trading volume in model with overhearing.

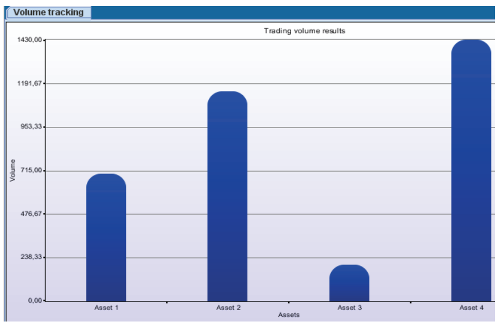

Figure 8: Assets trading volume without overhearing.

Table 3: Number of transactions per agent.

Agent	Transactions	Agent	Transactions
AI1	26	AIE11	9
AI2	20	AIE12	11
AI3	21	AIE13	14
AI4	31	AIE14	9
AI5	23	AIE15	10
AI6	0	AIE16	11

AI7	1	AIE17	4
AI8	0	AIE18	12
AI9	0	AIE19	10
AI10	18	AIE20	8

In our simulations, price evolution in the configuration with overhearing (Figure 9, 10) is less stable than that without overhearing (Figure 11, 12). This allows us to deduce that the mimicry between agents formalized by the introduction of overhearing generates a high volatility in the market.

Figure 9: Asset 1 price evolution with overhearing.

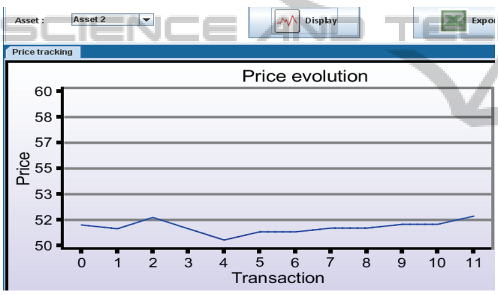

Figure 10: Asset 2 price evolution with overhearing.

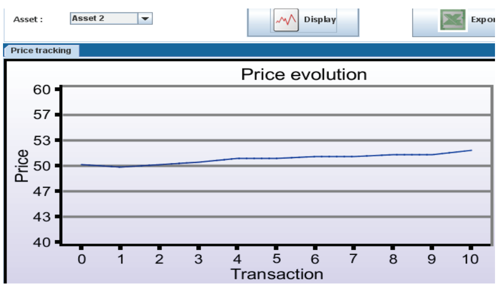

Figure 11: Asset 2 price evolution without overhearing.

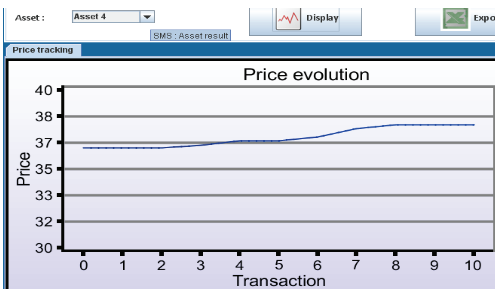

Figure 12: Asset 4 price evolution without overhearing.

The portfolio evolution of investor agents in the configuration without overhearing (Figure 13, 14) is relatively stable compared to that of investor agents in configuration with overhearing (Figure 15, 16, 17).

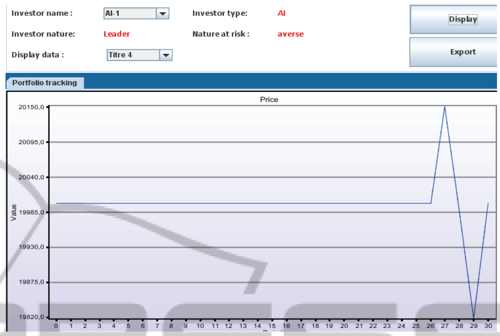

Figure 13: AI1 portfolio evolution without overhearing.

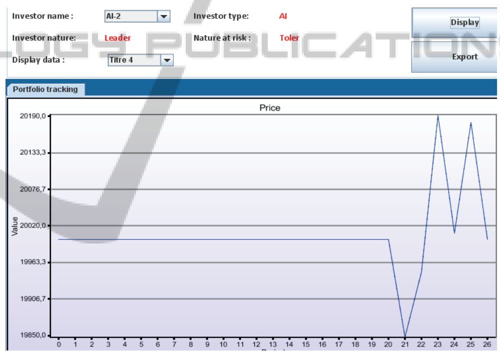

Figure 14: AI2 portfolio evolution without overhearing.

These results show that the instability of a market is caused by the mimetism phenomenon. The uncertain environment and the diversity of information in the market generate a variety of behaviours.

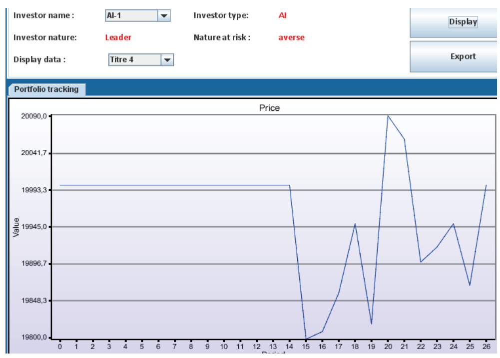

Figure 15: AI1 portfolio evolution with overhearing.

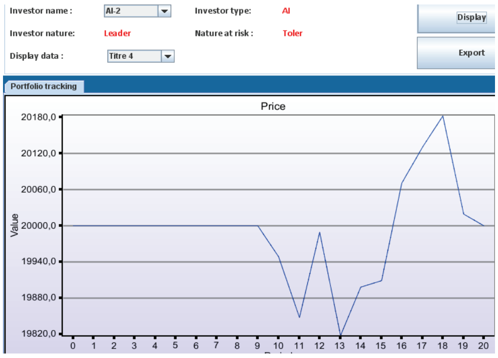

Figure 16: AI2 portfolio evolution with overhearing.

Figure 17: AIE19 portfolio evolution with overhearing.

The market liquidity i.e. there is at any time purchasing and sales agents is maintained by agents not based on overhearing according to the important number of their transactions. If overhearing is generalized in the market will certainly be less liquid and more instable.

7 CONCLUSIONS

In this work, we have shown the need to simulate financial markets in order to understand the emergence of complex phenomena as unpredictable as difficult to explain. We have analyzed different existing models of artificial markets, and found that most of them do not deal with order-driven financial markets. In addition, these models do not pay attention to the informal interactions between investors. So we designed and implemented a new model of order-driven markets, which operates asynchronously and in which agents have been endowed with sophisticated reasoning. The mental models of the agents are supported by classifier systems allowing them to learn from their experiences and thereby improve their decisions. These models have been tested, analyzed, and proved their efficiency in finding the best behaviours for investor agents. In addition, we have introduced in our model an overhearing mechanism by offering the opportunity to study the impact of informal exchanged information in a financial market. Through the proposed model, we have tested the impact of overhearing on the global dynamic of the market. We showed and discussed the results of simulations and conducted experiments. Our prototype can be extended and combined with a social network structure for studying recurring events in financial markets as speculative bubbles.

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