On The Design Of Artificial Stock Markets

Katalin Boer, Arie De Bruin and Uzay Kaymak

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Katalin Boer Arie de Bruin Uzay Kaymak

Erasmus University Rotterdam, Faculty of Economics

P.O. Box 1738, 3000 DR, Rotterdam, the Netherlands
e-mail: {kboer,adebruin,kaymak}@few.eur.nl

Abstract

Artificial stock markets are designed with the aim to study and understand market dynamics by representing (part of) real stock markets. Since there is a large variety of real stock markets with several partially observable elements and hidden processes, artificial markets differ regarding their structure and implementation. In this paper we analyze to what degree current artificial stock markets reflect the workings of real stock markets. In order to conduct this analysis we set up a list of factors which influence market dynamics and are as a consequence important to consider for designing market models. We differentiate two categories of factors: general, well-defined aspects that characterize the organization of a market and hidden aspects that characterize the functioning of the markets and the behaviour of the traders.

Keywords

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1 Introduction

Despite the large amount of research in finance and economics, the behaviour of financial markets is still poorly understood, and there is much controversy about the market mechanisms that lead to the observed price developments of the assets. Why would someone like to understand market dynamics? Investors and financial analysts, would like to understand them in order to make valuable investments. Market regulators need to understand them in order to improve market quality while scientists aim to test and state financial hypotheses.

In order to understand, manage and control market dynamics several models have been designed, that try to represent real markets of eventually part of real markets. Classical theoretical models (like the Capital Asset Pricing Model) and hypotheses (like the Efficient Market Hypotheses) idealistically describe and characterize market dynamics and traders' behaviour. The question is whether they represent the reality. Empirical and experimental studies are conducted to test the theoretical descriptions. The conclusion is that the standard finance models of rational behaviour and profit maximization can be true within specific boundaries, they are, however, incomplete, since they do not consider individual behaviour (Reilly and Brown, 2003).

Contradictions in the findings are ascribed to the differences in the assumptions made. Assumptions during market representation are, however, necessary given the large variety of real stock markets and the hidden feature of the details of the trading processes and participants' behaviour, aspects that make in fact dynamics difficult to understand.

We refer to any market model that in some way represents real stock markets, as *artificial stock market* (ASM). An artificial stock market is like any other model an external and explicit representation of part of reality (that are stock markets) as seen by the people who wish to use that model to understand, to change, to manage and to control the part of reality (Pidd, 2003). Several tools are used for representation, and based on them we distinguish three types of artificial stock markets: analytical, experimental and computational. In analytical models equations are used to describe market mechanisms. In experimental models, humans are used additionally to represent market participants, while in computational models market dynamics are represented by means of software programs. The approaches are further often used in a mixes way: laboratory experiments are often conducted with the participation of humans, that trade using a computer system, further analytical models are often so complex that they can be analyzed only with the help of the computers. The most innovative and most improved forms of computational models are the so-called agent-based artificial stock markets (ABASM), artificial markets where traders are represented as individual software components. This approach typically uses artificial intelligence technologies to represent the adaptive behaviour of market participants. The new and quite popular area that introduced this approach is referred to as agent-based computational economics (ACE), described in detail by Tesfatsion (2001).

In this paper we discuss what kind of market structures and behavioural representations are implemented in the literature and we analyze in which measure do the representations reflect real stock markets. For this reason we set up and introduce first a list of critical factors that define stock markets, based on the microstructure literature. We extend the list with behavioural components of the different market participants, derived from their role in the specific markets. The contribution of this paper is thus, the identification of a list of organizational and behavioural aspects that influence price formation and trading decisions. The identified factors serve as a guideline for comparing potentials of ASM's in the literature and for an overview of the structural and behavioural representation possibilities. Further they provide the main design issues one should consider when building new market models.

The outline of the article is as follows. First, in Section 2 and Section 3, we describe the structure and respectively mechanism of the stock markets in order to identify the most important factors that influence market dynamics, and therefore one should consider for designing artificial markets. Then, we analyze which of the identified organizational, in Section 4, and respectively behavioural factors, in Section 5, are considered and how are they represented in several existing ASM's in the literature. Finally, in Section 6 we discuss how representative these markets are and propose a new flexible, framework for representing stock markets with view on the varying and ignored features.

2 The organization of stock markets

Artificial stock markets are primarily designed with the aim to help us to understand and study market dynamics. Market dynamics can be studied through price dynamics (usually in form of returns). Prices in general are directly determined by the price formation mechanism that applies on a specific market, they are however indirectly influenced by several other known and partially observable factors (economy, news, financial situation of equity issuers, personal

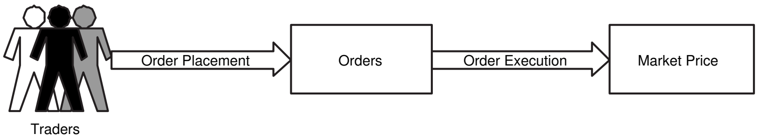

Figure 1: Price formation at high level

opinions, etc.) through the traders' behaviour (Figure 1). Price formation mechanisms are basically *order* execution mechanisms, since market prices are formed as a result of executing (matching) orders.

In order to find out how to design artificial stock markets an overview of the structure and workings of real stock markets is required. While several studies ignore the importance and influence of the market structure on price formation the market microstructure literature aims to study the effects of this relationship (O'Hara, 2002). The institutional structure behind price formation might be ignored for some purposes, like when longer investment horizons are involved, however, for other purposes (measurement of execution costs, market liquidity, comparison of alternative market making mechanism, etc.) market microstructure should be central (Campbell et al., 1997). Market microstructure investigates trading and the organization or structure of markets. The structure of a market is defined by trading rules and trading systems and determines who can trade, what, when and how can be traded, and further what traders can know and do in a market (Harris, 2003). The structure provides the framework within which the market functions, that is trading takes place.

In this section we try to identify the main *organizational factors* that govern market dynamics and as such should be taken into account when designing artificial stock markets. Based on the aspects discussed by Harris (2003) and Madhavan (2000) we identify the following main factors that describe a market structure: traded instruments, order forms, trading sessions, execution systems, protocols, transparency and market participants. We elaborate on each of them in the remaining of this section.

2.1 Traded instruments

At every market it is well-defined what kind of instruments can be traded. Instruments include several types of assets and contracts. Real assets, for example, represent physical commodities or machines. Financial assets are instruments that represent ownership of real assets and the cash flows that they produce. Stocks are financial assets that represent ownership of corporate assets, net of corporate liabilities (Harris, 2003). A given stock can be traded on a market only if it qualifies for listing, that is it, and the corporation that issued them, satisfies certain criteria stated by market rules. On the NYSE, for example, approximately 3200 stocks were listed in 2000 (Reilly and Brown, 2003). Some stocks can be traded on more than one market.

As stock are traded on markets, they are priced according to the rules that hold on the market organization. Their value, however, depends on the valuation of corporate assets, liabilities and income of the corporation that they represent, and further on the traders expectation of traders regarding how well they expect corporate managers will use corporate assets in the future (Harris, 2003). In this sense stocks are not integral part of a market where they are traded, but, they exist ”outside” the market. They represent the issuer company, dividends are payed on them and are valuated (besides their market performance) according to the issuer’s plans and financial situation.

2.2 Orders

Trading intentions are expressed by means of trade instructions called orders (Harris, 2003). There are various types of orders defined depending on the details that they contain: limit, market, stop, block, etc. (Madhavan, 2000). Orders specify which instrument to trade, how much to trade (size of an order), whether to buy or sell (side of an order). All this information is contained by the most simple orders, called *market orders*. Orders might additionally specify some conditions that the trade must satisfy. Conditions might refer to the ultimate price (limit price) that the trader accepts for an order, in case of *limit orders*, and they might further indicate for how long the order is valid (expressed in time or related to change in the market price), whether the order can be partially executed, etc.

Orders are either sent from one participant to another or to a system for handling, or are just made public and wait for execution initiated by others. Orders of some participants, made public in order to indicate the number of shares and the price for which they are willing to trade a certain stock are defined as *quotes*. Orders expressing willingness to buy are *bid quotes*, while orders expressing willingness to sell are *ask quotes*. Buy and sell orders that can not be executed for the moment are entered in a so-called *limit order book*, hold for every stock. Whether and in which measure is the content of a limit order book available to the market participants and other restrictions regarding order placement are determined by the protocols that hold on a market, described in Section 2.6 and further, depend on the grade of transparency, discussed in Section 2.7.

2.3 Market participants

In every market it is well-defined what kind of traders can operate, their number, role, obligations and restrictions. Depending on their tasks and role in the market we classify different market participants (traders) in two main groups: *investors* and *financial traders*. We refer to traders who are not part of the market organization itself, as investors. They are simple traders, such as individuals, mutual funds, money managers or corporate pension funds (Harris, 2003). Financial traders, also referred to as financial agents in the financial literature, are traders endowed with special role in the financial market. There are several types of financial agents endowed with different tasks based on the market microstructure where they interact.

Financial agents need to conduct basically two tasks: to execute orders on behalf of the clients or to execute orders for own account in order to provide liquidity. In this way we further differentiate two types of financial traders: brokers and market makers.

Brokers are primarily required to execute orders for customers. They might be allowed at some markets to trade for their own account as well.

Financial traders responsible to provide liquidity are referred to in the literature as *dealers* or *market-makers*. They might represent the ”Specialist” from the NYSE, the ”Hoekman” from the Amsterdam Stock Exchange, the ”Kursmakler” from the Deutsche Börse AG, and dealers from OTC markets, like the Nasdaq.

There are one (e.g NYSE) or more (e.g. NASDAQ) market-makers assigned to each stock responsible for liquidity depending on the market. At most of the markets market-makers have to provide *bid and ask quotes* for the stocks for which they are responsible for. If more market-makers are assigned for a certain stock (e.g. dealers on Nasdaq), they are competing with each other by trying to provide the best bid-ask quotes.

The following relation holds between different market participants (Figure 2). Market makers function on the market itself, brokers however can work also independently and have contact with member brokers from the market organization or directly contact market makers if they want to trade. Investors typically contact a specific broker or brokerage firm if they want to sell

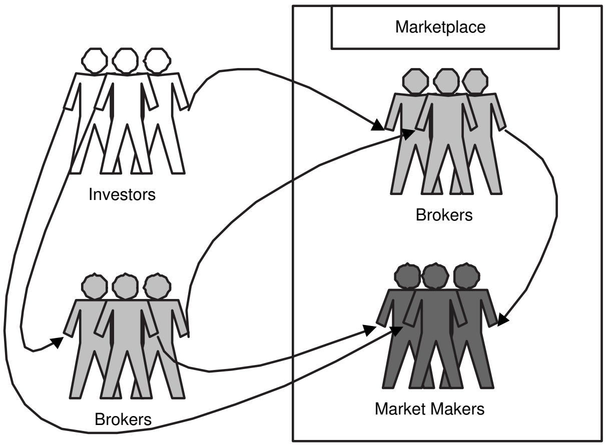

Figure 2: Relation between traders

or invest, and ask their advise and help to place orders. However, it can happen that investors, if they are, for example, member firms, or trade via electronic trading systems, trade directly with the market maker. Brokers on the market might be allowed to take or not public orders. In a common situation brokers are contacted by investors to execute an order, they further try to trade with other brokers or market makers, like the specialist on NYSE, and the dealer with the most attractive quote on Nasdaq. Market-makers have to execute orders that arrive from outside the market-place or from brokers that could not have been executed. They might execute the overtaken orders either immediately or later, based on market requirements, their strategy and belief. If orders can not or are not executed immediately they are entered into the limit order book that exists separately for each stock.

At some of the markets it might be the case that the final execution of the orders and the final price setting is not managed by financial traders, but it is solved by a sort of automated order matching system. We will discuss this later, first let us see how can trading and order execution be organized at various markets.

2.4 Trading sessions

Trading at stock markets takes place in trading sessions (Harris, 2003). There are basically two types of trading sessions, based on the degree of continuity (Madhavan, 2000): call market sessions and continuous sessions. On *call-markets* trading occurs at specified times, when all the placed trading requests for a stock are aggregated and a single price is set, usually such that the trading volume is maximized. On *continuous markets*, trading can occur at any time the market is open.

Although there are several types of stock markets, there is some tendency to converge towards similar organizations (Demarchi and Foucault, 2000) and some structures are adopted by more markets as they seem to lead to more efficiency. In this sense, active or otherwise *liquid* stocks, for example, are usually traded on continuous markets, while less liquid stocks through call mechanisms. Additionally, there is a general convergence towards a structure where call markets are used to open and/or close the trading day and continuous mechanism is used in between (Demarchi and Foucault, 2000). On continuous markets call sessions are also applied during trading suspensions, that are entailed by extreme changes in the prices, usually caused by the release of some significant new information. According to Reilly and Brown (2003) the temporary use of call market mechanism contributes to a more orderly market and less volatility.

2.5 Execution systems

The execution system or trading system of a market defines the mechanism of order execution, that is the way buyers are matched to sellers (Harris, 2003). Execution systems are mainly quote or order driven.

On *dealer* or *quote-driven markets*, special traders, called dealers, endowed with the role to provide liquidity, trade for own inventory by placing quotes at which they buy and sell. Basically dealers must participate in every trade.

On *order-driven markets* buyers and sellers can directly trade together. Order driven markets often take a form of an auction. On *auction-markets* or *price-driven* markets the trading rules formalize the process by which the buyers seek the lowest available prices and sellers the highes available prices. Trading requests are submitted to a central location, where they are matched (Reilly and Brown, 2003; Madhavan, 2000). On call markets typically single-price auctions are conducted, collected orders being matched at the same, single price, and accordingly the call-sessions are typically referred to as call-auctions. This form of execution mechanism, for example, does not necessarily imply the management of a specific financial trader. On some continuous markets continuous two-sided auctions are conducted, in which buyers and sellers can continuously attempt to arrange trades (Harris, 2003).

Most of the markets do not apply a single execution system, but they combine dealer and order-driven markets. In situations like this the dominating system defines the market type. The

Nasdaq Stock Market is, for example, a quote-driven market, in which sometimes traders can directly trade together. Further, many continuous markets combine trading systems, in the sense that they are basically order-driven markets but if there is not enough activity intermediaries intervene as dealers (Reilly and Brown, 2003).

2.6 Protocols

Protocols refer mainly to the rules adopted on the market, such as the time of the call-auctions on continuous markets and restrictions regarding the orders and quotes that traders can place(Madhavan, 2000). Market rules might specify for example, the minimum number of shares for which the quotes must be made. On the Amsterdam Stock Exchange for example there is a minimum amount determined (Demarchi and Foucault, 2000). Further, they can restrict the allowed minimum and maximum difference between the bid and ask prices of a dealer's quote, called as *bid-ask spread*, the minimum/maximum price increment/decrement between two consecutive bid/ask values, the unit by which dealers can vary their quotes (e.g. decimals) called *tick-size*, etc. Protocols can vary not only from market to market but from stock to stock within a market as well, usually based on the grade of liquidity of each stock.

2.7 Transparency

Transparency refers to the quantity and quality of information provided to the market participants during the trading process (Madhavan, 2000) and further, to the extent of dissemination and speed of dissemination (Demarchi and Foucault, 2000). Information is classified as pre-trade or pro-trade based on the timing of its availability. Pre-trade information refers to information a-priori available for traders, such as: quotes, the content of the limit order book, degree of anonymity. Post-trade information refers to the made transactions, the publication of prices, etc. Transaction data is, for example, is a post-trade information, that is often published with some delay on many markets, for example in case of large transactions.

The organizational factors described above state how trades can be made and thus, how prices can be formed on a market. However, they do not make public the detailed process of how prices are actually formed. The final price is determined by the execution system applied on a market. Several possible forms and implementations of a sort of execution system might exist, the details of which is not revealed by the market organization. The final price formation process is even more intricate if it is not mechanic, but involves a market participant, like a market maker (LeBaron, 2001). The presence and behaviour of traders is constrained by the way a specific market is organized, however, their actual behaviour is again individual and autonomous and is determined by the de facto functioning of a market. According to this observation, next we aim to discuss the possible trading behaviour of market participants, differentiated according to their role, in the view of the market organization where they interact.

3 Behavioural factors influencing market dynamics

In this section we aim to identify behavioural aspects that influence market dynamics. Behavioural aspects are related to the type and form of decision of market participants acting in some market environment that functions based on its organization. Accordingly these factors concern, for example, the way market participants decide which stocks to trade, the way they determine the parameters of their orders and quotes, their timing regarding when to place orders, when and how to provide liquidity, how do traders involved in the mechanism of the execution system determine the parameters of a transaction, if that is not unequivocally defined by the description of the system, and so on.

The difficulty of understanding market dynamics arises from the presence of two (partially) ”black-boxes”, that is the price formation mechanism and the decision making mechanism of the traders. The former is more related to the organization of the market, especially to the execution system applied, the latter to the behaviour of market participants. The two black boxes are however strongly related to each other, given that market participants might be involved both in placing orders and executing them (Figure 3).

It is not difficult to observe the trading actions, that participants take. What is more problematic is to define what governs these actions, such as when, how and why do participants take these actions, how do they determine the parameters of the orders. How traders solve these problems depends on their role in the market, the market structure, and some individual characteristics. The methodology that we apply for deriving the behavioural factors is to watch markets in action, that is to observe possible ways of price formation through the behaviour of market participants by tracking step by step how orders can trigger market prices.

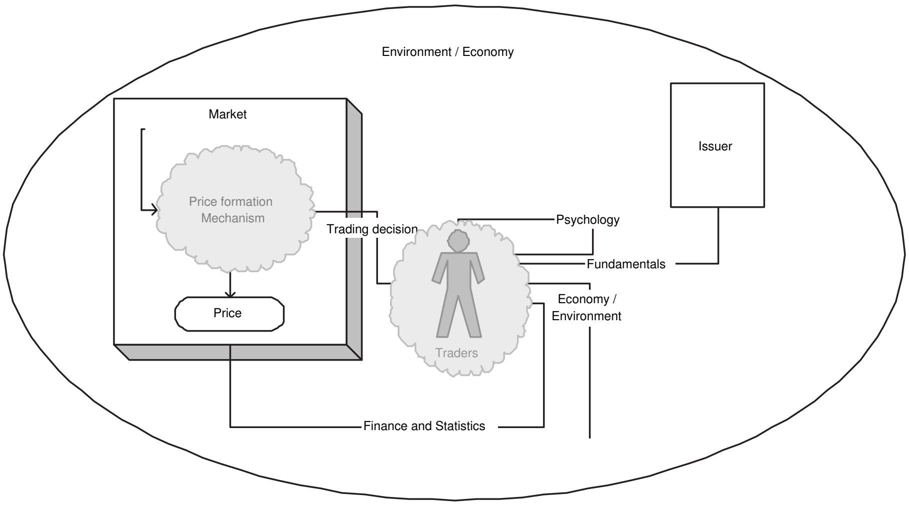

Figure 3: Processes that determine market dynamics at high level

3.1 Order-placing behaviours

Orders are primarily initiated by investors or by financial agents trading for own account. In case of investors order placement is a result of the portfolio management process, while in case of financial agents it is mainly triggered by their role in the market; that can be, for example, the commitment of brokers to execute an incoming order, or their current position in the market; often combined with portfolio management. The portfolio of a trader defines the composition of the instruments he/she holds. During the portfolio management process, traders aim to change the current composition of their portfolio.

The main question is, how traders determine the desired content of a new portfolio. As described by Reilly and Brown (2003), the portfolio management process involves four main, highly interrelated steps: the construction of a policy statement, the determination of the investment strategy to meet the policy statement guidelines, the construction and maintenance of the portfolio and the continual monitoring of the needs and conditions. We base our discussion mainly on this description.

3.1.1 Policy statement

The policy statement is a road map that specifies the investment goals, constraints and risks investors are willing to take. It depends on the expectations and experience of the investor and it is determined with focus on the investor's short-term and long-term needs. The policy should be updated from time to time given that needs change over time. Three main factors drive the policy statement: the investment goals, investment constraints and risk.

Investment objectives. Investors can have a variety of objectives changing over time. They all have different priority and are stated for different time-horizons. As a matter of fact, and as we will see later time-horizon is a factor that plays an important role during all the whole portfolio management process. Objectives vary from near-term high priority goals (such as accumulating funds to make a house down payment or pay college expenses) and long-term high-priority goals (like the ability to retire at a certain age) to lower-priority goals (like to take a luxurious vacation every year). Objectives depend and are constrained by several personal, financial and economic factors.

Investment constraints. Constraints that influence investment objectives include: liquidity needs, time-horizon, tax concerns, legal and regulatory factors, unique needs and preferences. A close relationship exists between an investor's time horizon and liquidity needs. Near-term goals might require quick conversion to cash and thus more liquidity.

Attitude to risk. People are willing to take different grades of risk in order to achieve the stated objectives. Besides the priority of an objective, the personal preference, and the financial constraints of an investor, the time horizon might influence a lot the ability to handle risk. In this sense long investment horizons can usually tolerate more risk, while investors with shorter time horizons favor less risk.

3.1.2 Investment strategy

In order to achieve the investment objectives stated in the policy statement traders develop a variety of investment strategies. The development of a strategy includes the study of financial, economic, political and social conditions and aims to **forecast future prices** in function of time. Many indicators exist that traders use for analysis in this sense. Besides many studies, an overview and motivation of possible stock characteristics is given by Haugen (2001). Indicators are characterized as either technical or fundamental. Fundamental indicators are related to the basic intrinsic value, also referred to as fundamental value of a stock, and as that depend mainly the underlying economic factors(Reilly and Brown, 2003), like the performance of the issuer. Technical indicators refer to assumed statistical features of historical data. Arbitrary many ways exist to consider and combine diverse indicators in order to have a possible projection into the future. Based on the type of data that is used by traders for fore, two main types of investors are differentiated: *fundamentalists* and *technical analysts* (or chartists). They are also referred in the theoretical literature as informed traders and respectively noise traders.

3.1.3 Portfolio maintenance

Based on the policy and forecast, traders or their advisors implement the investment strategy and determine how to allocate available funds across different markets, asset classes and assets with view on the investor's attitude to risk. Trading instruments of different types are categorized in asset classes (e.g. real assets, risk-free assets paying constant interest rate, stocks paying varying dividends). Independently from the investment strategy used, the portfolio construction results in **asset allocation**, that is, the determination of the required:

- **asset classes and weights** for each class
- **specific assets and weights** of them within each asset class

The composition of the required portfolio depends, besides the strategy, on the attitude to risk and preferences of the participants. It seems that it is more important (regarding investment performance) to select the right composition of the asset classes than the specific assets within classes.

The difference between the current portfolio and the required portfolio leads to the **orders** that traders will place. The difference defines the identity of the traded assets, the size and side of the orders.

Price quote. When placing an order traders should have in mind an ultimate price at which they are willing to buy/sell the selected stocks. The price depends a lot on the expectations given by the investment strategy. At markets where limit orders can be placed, traders can quote a price (limit price) at which they are willing to trader in worst case. Traders might also decide to place market orders, and then, the price that they are not willing to exceed can be determined by the right **timing** of the placement of the order.

3.1.4 Monitoring

Monitoring in fact is not conducted apart from the other steps of portfolio management but can be included in and affects the whole process implying the periodic reconsideration of the various phases. Investors monitor their needs and the market conditions, and evaluate the portfolio performance from time to time, compare it to expectations, and modify the policy statement and/or the investment strategy if they think it is necessary. Monitoring includes thus, **performance analysis**, the assimilation of new **information**, and further, the resulted update of the statement and strategy reflects the **adaptive** behaviour of the traders.

As can be observed, **time factors** related to different decision problems play role during the different steps of portfolio management process. Timing in this sense has multiple dimensions. Besides the timing of the trading sessions that apply on a market, it can refer to the time-horizon of the investment objectives of the traders, to the forecast horizon of the investment strategies, to the time limit traders look back in past for relevant historical data for forecast reasons, to the time at which they decide to place an order for a certain stock, their waiting patience for the execution of a limit order, to the time they monitor changes and decide to reconsider their strategies and objectives, and so on. Decisions related to timing can be influenced by current market conditions but also by several individual factors, such as: goal, belief and portfolio composition. The timing with respect to the placement of an order is, for example, determined by the internal characteristics of a trader, the signals/information perceived and by the market regulations. Alternatively, brokers might advise their clients (investors) when they think it is advantageous to place an order for a certain asset.

Above, we analyzed the order placing behaviour of investors, that is related to the portfolio management process, as described by Reilly and Brown (2003). Based on the market organization where they interact, brokers and market makers might deal with similar decision problems. Order-placing can be additional to them, but mainly is related to, and can be entailed by the order execution behavior required by their role. In the next subsection we continue to trace the orders on the various routes they can follow based on the organization of the market where they are placed and executed and on the type and behaviour of financial traders who overtake and execute them.

3.2 Order execution mechanisms

3.2.1 The order-routing and order-execution behaviour of the brokers

Besides placing orders for own account if allowed, brokers **receive orders** placed by investors and try to execute them. The main decision problems that brokers, who according to their role are committed to clear orders on behalf of the investors, face are:

- which received order(s) to select for execution; and
- how to execute them?

Such as investors, brokers continually **monitor** and analyze the market conditions which influences them in making decisions. The way brokers decide to select and execute orders depends on the execution system(s) applied on the market where they interact.

The order selection strategy. Brokers might try to execute orders one by one or in an accumulated way. Orders that are not immediately executed are stored in an order book, and selected from here later, for further execution. The selection choice can be based on the order of arrival, price (orders with higher probability for execution might be chosen first) or more orders can be aggregated, and a new order can be created that contains and represents them. It is not clear how brokers solve this problem in reality, arbitrary many possibilities exist, which depend on several individual and financial features. Further, the way selection is made is influenced by the execution system that is applied on a market.

The execution mechanism. For an easier overview assume $Broker\_A$ receives and executes orders one by one. Suppose he receives $Order\_X$ from $Investor\_X$ and thus needs to execute it. The broker needs to decide through which available execution mechanism to execute the received order. There are basically three main possibilities he can choose from (Figure 4) depending on the rules and execution system that apply on that market(U.S. Securities and Exchange Commission, 2001):

1. execute the order or part of it internally (represented by $Order\_X^I$);
2. try to find other agents that are willing to take the other side of the order preferably at an improved price ($Order\_X^N$);
3. submit the order for further execution to a central execution system ($Order\_X^D$).

The first two choices can be made, for example on order-driven markets, where participants can directly trade with each other. The central execution system where orders can be sent and cleared can be, for example, a sort of automated central matching system on call-auctions, or might represent and be driven by market makers, who quote bids and asks and maintain a limit order book on quote-driven markets.

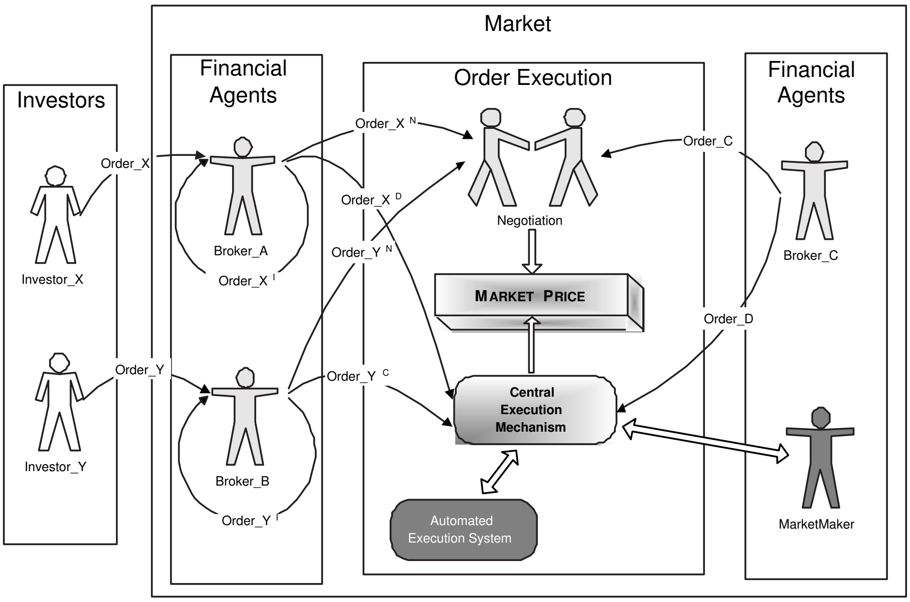

Figure 4: Tracking orders

Depending on the decision of $Broker\_A$ $Order\_X$ might be transformed to one or more other orders before final execution. Transformation might be applied to volume and/or price. It is often possible to improve the execution price or to clear first only part of the order, and later the rest, probably at a slightly different price, and even through another execution mechanism.

1. If a broker is allowed to and chooses to execute the order internally, he needs to decide further, whether to match the order with orders sent by other traders (that could not have been executed previously) or execute it for own account. If brokers take the other side of an order they might encounter surplus/deficit in their inventory, and will be faced with a portfolio management problem similarly to the investors. Order execution might thus trigger additional orders.

2. If the market organization makes possible and the trader chooses to find other financial agents to trade with, he can either accept an offer of the others or try to negotiate. If negotiation is considered he further needs to set up some kind of **negotiation strategy**, that involves decisions regarding:

   - timing related to the length of negotiation: for how long to try to negotiate an item?
   - the negotiation steps: how to define the negotiation prices?
   - timing related to the negotiation patience: how long to wait before making the next

bid/offer?

- negotiation limit: when to accept another offer?

Negotiation, in form of continuous double auction, is for example an execution system applied at the NYSE and is introduced with the aim to improve the execution prices of orders.

3. If the broker routes the order for execution to a central order execution mechanism he can still send it with an improved price quote. In this case it is up to the execution system how it clears the order. How this can be done is discussed in the next section. The decision brokers have to make in this case is related to the timing factor, namely: for how long to keep an order before sending it to a central matching mechanism. In most of the cases this is not a difficult problem since it is often specified by protocols for how long can brokers at the trading floor keep an unexecuted order.

Independently of the made choice brokers have to determine the **transaction price** at which to execute the orders in case of actual execution, or a **price quote** in a way similar to investors, in case of routing the order. The price depends on the price quote that the requesting investors set, in case of a limit order, but also on the current market conditions and regulations.

Similar to the variety of investment strategies that can be applied by investors, arbitrary many realizations of the order selection and the execution strategy of the brokers exist. Several possible variants (of e.g. negotiation strategies) are described in the literature, however, except for the constraints defined by market organizations, details of the applied strategies are not made public by the brokers themselves.

3.2.2 The order-execution behaviour of market makers

The role of market makers based on (Madhavan, 2000; Reilly and Brown, 2003) and (Demarchi and Foucault, 2000) is to

- supply immediacy in order to permit continuous trading by over-coming the asynchronous timing of investor orders;
- monitor the market through quoting bid and ask prices at which they buy and sell stocks, so that traders do not need to expend resources to do that;

- set prices: adjust the bid-ask spread to the changing market conditions;
- provide liquidity: provide additional liquidity for small capitalization or less liquid stocks;
- in some cases (must) complement the supply of liquidity at the time of call-auctions: this can lead to equilibrium and liquidity;
- might promote small stocks (either as obligation or as incentives): give away information regarding stocks in which they make market.

Summarizing the tasks above, market makers are responsible for a good functioning of the markets, and for this reason, they need to place additional orders and to execute the received orders as soon as possible, and need to maintain bid and ask quotes that on the one hand reflects market conditions, and on the other hand encourages trading. When market-makers receive an order they check whether it matches the quoted bid (in case of a sell order) or ask (in case of a buy order). If it matches they clear the order at the quoted price and charge the actual transaction costs, otherwise they enter the new order into the limit order book. Besides new order arrivals, inactivity on the market, competitive behaviour, belief, or the arrival of some information, can cause the market maker to update its bid/ask quotes. The main decisions that market makers face is thus related to the:

- **determination of the new quotes**: what should be the values of the new quotes so as to reflect the content of the limit order book, the position of the market makers and to ensure a liquid and fair market?
- **timing of the new quotes**: that is when, in which case to change the quote. How to decide that there is not enough liquidity? How to be competitive without loosing in case of competitive markets?
- **how to manage the limit order book**, that is how and when to execute orders entered in the limit order book? This problem is related to the way new quotes are determined, since market makers can take the other side of an order before they make new quotes, or after some quotes are executed, in order to ”recover” their position. Further, at some markets, like the French stock exchange (Demarchi and Foucault, 2000), (part of the) limit order books is public, and traders can thus formulate their orders (and limit prices) in such a way to match some of the orders from the limit order book if they wish to.

The most simple solution for defining a quote is to take the highest bid and lowest ask orders from the order book, as quotes. Real bid-ask setting strategies of market makers are in fact, probably much more complicated, as they depend, besides a lot of factors, for example, on the content of the limit order book and on the position of the market maker as well. How each market maker determines the quote can vary a lot again.

Market makers as defined and described here are primarily specific, and have a decisive role on (continuous) quote-driven types of markets. The way orders are executed on order-driven, and especially call-auction types of markets is briefly discussed in the next subsection.

3.2.3 Automated execution of orders

Not all the execution mechanism imply the intervention of a financial agent. A mechanism on continuous markets where limit orders are stored if they cannot be executed and new orders are matched against the best quotes, for example can be solved by an automated order matching systems, where actually market makers do not have to be involved. This is obviously the working mechanism of continuous electronic systems working 24 hours a day.

Automated order matching can be especially be applied during call market sessions, where, as described in Section 2 trading takes place at well defined times and all interested traders in this case thus need to send their orders at well defined time to a central execution system. In case of call auctions orders are accumulated and matched at a single price at some equilibrium. The equilibrium point can be defined in different ways but in most of the cases the aim is to maximize trading volume, or to minimize excess demand. The key-factor that makes the mechanism of call-auctions to differ is thus, the:

- **determination of the equilibrium price**: namely, how is the equilibrium price set.

Central order execution can be conducted by a special financial trader, e.g. market maker but usually an automated system is used to solve it. The precise details of the matching are however, again, not completely publicly known.

3.3 Summary

In this section we tried to follow the possible life cycle of an order. As can be concluded form the previous sections, although the organization of a market (trading rules and mechanisms) might clearly define how prices are set, it is not obvious how prices are actually determined as several possibilities exist. We summarize in this section, the possible forms of execution of an order and the market prices that the original order could trigger. It is important to make a clear distinction between the originally quoted price of an order and the final price that an order triggers. We refer to a limit price that investors (or other order-initiators) define as a *price quote* or quoted price, and to a price that is a result of a transaction as the *market price*. Based on the organization of the market and the behaviour of participants a final market price might be set:

- by the broker within own account
- by brokers through negotiation
- by the market maker at quote
- by an automated electronic system based on submitted quotes
- by the market maker at equilibrium
- by an automated matching mechanism at equilibrium

How investors, brokers, market makers or automated electronic systems actually determine a price can vary a lot, because of the multitude of solutions that can exist, and additionally given the ”bounded rational” feature of the financial traders. Tracing the path an order takes till it is executed shows that a multitude of factors might influence the value of the resulting market prices. The final market price does not only depend on the originally quoted price of an order placed by an investor but might go through slight changes based on the market structure, financial agents’ role and behaviour.

We have identified several organizational and behavioural factors that are often hidden and often vary underlying the differences between various markets and traders’ behaviour respectively. By hidden factors we mean, values and processes that are not revealed by markets and traders. The hidden feature of the market mechanisms together with its dynamic feature present difficulty to understanding market dynamics. This is further the reason why in order to study and understand market dynamics, representations of markets should be designed with assumptions regarding these hidden features. In the next section we trace the list of the influential factors identified and discuss how artificial stock markets in the literature consider and represent them.

4 Organization of Artificial Stock Markets

As discussed in the introductory part of this article, we refer to any model that in some sense represents the organization of stock markets as an artificial stock market, regardless of being analytical, experimental or computational. The criteria for selecting the ASM's that we study here is, next to a price formation mechanism, the representation of the behaviour of traders in some measure as well. In order to find the ASM's first of all, we take into account the references from the ACE website, references from the studied articles and, search articles in journals that contain articles about market models and additionally make use of search engines. We do not say the list is complete, but it reflects the main research directions and represented market organizations. The list consists of the following focused artificial stock markets:

- CLM: the artificial financial market presented in (Chen et al., 2001);
- Farmer: the agent-based model for investment in (Farmer, 2001);
- MDS: a microscopic dynamical model (Daniels et al., 2002, 2003; Smith et al., 2002);
- ABS: the Adaptive Belief System (Brock and Hommes, 1998; Hommes, 2001);
- Genoa: the Genoa artificial stock market (Raberto et al., 2001; Cincotti et al., 2003);
- MF: the financial market in (Franci et al., 2001) and (Matassini and Franci, 2001);
- CTAM: the Continuous Time Asynchronous Model introduced in (Shatner et al., 2000);
- SantaFe: the Santa Fe ASM as described in (LeBaron, 2002) and (Tesfatsion, 2004);
- BS: the business school representation in (Chen and Yeh, 2001);
- Das: the microstructure model in (Das, 2003);
- EM: the ASM based on electronic market maker in (Chan and Shelton, 2001);
- KapSyn: the KapSyn framework based on (Loistl and Vetter, 2000);

LeBaron elaborates on six design issues needed to consider for building artificial stock markets: agents, trading, securities, evolution, benchmark/calibration and time (LeBaron, 2001). The organizational and behavioural aspects that we have defined cover the first three issues;

even in an extended way, as we look at the complete market structure and not only trading; and partially touch upon the last three issues. The details that are elaborated by LeBaron (2001) and are not discussed above are more implementation related and, therefore, we do not discuss them here.

Taking into account the two categories of factors described in the previous two chapters we analyze the design and mechanism of several artificial stock markets in two sections: first we describe how organization elements are designed in the literature and then we discuss the variety of applied price formation and order execution mechanisms, and the related traders' behavioural representation.

This section is based on the organizational aspects discussed in Section 2 and concerns mainly the trading issue from the list composed by LeBaron, however since we apply the market microstructure approach we touch upon the time issue and on constraints regarding the market participants and assets (securities) that are allowed to be traded.

The most realistic way of modelling a system (in this case a stock market) would be to represent every detail, to precisely implement its whole structure. This representation seems, however, impossible given the variety of complex structures and mechanisms of stock markets and further the presence of several hidden factors and processes that are not (or cannot) be revealed. Further, in order to study the effect of some specific factors on the market dynamics, we need to exclude other ones, reason for which controlled environments are needed in which influential factors can be added and modified in a flexible way. This constructive representation is related to the study of market dynamics as emerging from interactions of individuals, the governing principle of the agent-based computational economics (ACE) approach (Tesfatsion, 2001; LeBaron, 2000). The chosen market structure, the simplifications and approximations made depend of course on the aim of the research. The consequences of the choices made need to be examined however. In this section we summarize how ASM's deal with the choices regarding the architectural elements. A structured overview of the organization of the studied markets is provided by Table 3.

4.1 Traded assets

Although hundreds of securities are traded on stock markets, ASM's consider only few of them in order to keep the experiments under control. Usually two types of assets are traded on artificial stock markets: one risk-free and one risky stock (Table 3). Multiple (risky) assets can be traded at the Genoa (Cincotti et al., 2003) and KapSyn (Loistl and Vetter, 2000) markets. In (Cincotti et al., 2003) experiments with two stocks are conducted, while in (Loistl and Vetter, 2000) the number of stocks can achieve 122, limited by computational implementation. Risk-free assets might represent mutual funds or bonds paying a constant interest rate, in most of the cases they represent, however, the cash reserve of traders. Risky assets usually pay stochastic dividends, as illustrated by the BS (Chen and Yeh, 2001), CTAM (Shatner et al., 2000), SantaFe (LeBaron, 2002; Tesfatsion, 2004) and ABS models (Brock and Hommes, 1998).

4.2 Orders

ASM's usually choose to express trading intentions of traders either by market or by limit orders. These are mainly the most common orders at stock markets as well. In artificial markets representing call-auctions (see Section 4.4), with exception to the Genoa market described by Matassini and Franci (2001), the initiated orders are market orders. At the Genoa market, mainly limit orders are generated, but, traders have the possibility to convert them to market orders. Further, orders at Santa Fe are actually demand functions of investors regarding the risky asset in function of the possible stock prices.

On continuous markets limit orders or both limit and market orders are placed. Limit and market orders are both placed in (Daniels et al., 2002; Chan and Shelton, 2001) and in (Matassini and Franci, 2001), market orders being matched against the quoted bid and ask, limit orders being entered into a limit order book. In (Das, 2003) and (Chan and Shelton, 2001) investors place market orders and the market maker places limit orders (bid and ask quotes thus). In the KapSyn market, limit orders are generated, but traders might also decide to accept another order, which is in fact equivalent with placing a market order. Unexecuted orders at the markets described in (Shatner et al., 2000; Loistl and Vetter, 2000) and (Daniels et al., 2002) can be cancelled if wished. Further, the parameters of the orders placed at the Genoa market can be changed by the traders (Matassini and Franci, 2001).

4.3 Market participants

Traders in the studied ASM's typically perform one action: they place orders as the result of some decision (that is mainly utility maximization at every point in time). These traders represent in this way only investors. In several studies investors are represented by simple equations, that illustrates there trading decisions (Hommes, 2001), or just the placed orders are modelled that arrive according to some distribution (Farmer, 2001; Chan and Shelton, 2001). Individual investors with more complex decision-making behaviour are represented, for example, in (LeBaron, 2002; Chen and Yeh, 2001; Loistl and Vetter, 2000; Shatner et al., 2000) and (Matassini and Franci, 2001).

Given that mainly call-auctions are modelled, the final order execution is often solved by an automated execution system, and as a consequence financial agents are rarely modelled. Brokers who commit themselves to execute orders for others are not represented in the majority of the studies. In fact, we found one single study where the role of the brokers is recognized and brokers are represented, that is the KapSyn framework presented by Loistl and Vetter (2000).

Market makers are considered in a few studies. At the Santa Fe ASM orders are aggregated and the market price is defined by a so-called auctioneer (LeBaron, 2002), who actually carries out an automated execution. In (Das, 2003) and (Chan and Shelton, 2001) the market maker is implemented based on the Glosten Milgrom model from the market microstructure literature (O'Hara, 2002). Further, market makers from XETRA are modelled in KapSyn.

4.4 Trading sessions

As described in Section 2 trading sessions are defined in function of time, that specifies when it is allowed to trade. Trading and time issues, thus, as defined in the design list by LeBaron (2001) are strongly related.

- Call-market sessions.

  At most of the ASM's trading takes place at discrete points in time in repeated sessions. In markets described in (Chen and Yeh, 2001; Yeh, 2002; Cincotti et al., 2003; LeBaron, 2002) and (Brock and Hommes, 1998), for example, traders or a (randomly) selected groups of traders simultaneously place orders at every simulation time. This implementation corresponds to the call-market sessions applied at financial markets.

- Continuous sessions.

  Several ASM's implement continuous trading sessions by centrally selecting one trader from the crowd whose decision is considered and whose order is executed if possible. In

(Matassini and Franci, 2001) and (Shatner et al., 2000) a randomly selected trader makes a trading decision (place, accept or cancel an order) which is carried out. In (Smith et al., 2002) and (Chan and Shelton, 2001) a microscopic dynamical statistical model is developed that implements a continuous double auction trading mechanism under the assumption of random order flow (modelled as Poisson processes).

At the KapSyn stock market agents simultaneously make decisions regarding which action to take next, based on given market characteristics, utility functions, reaction, and implementation time related to actions. At every ”simulation” round, however, only one agent with a correspondent action is selected for execution. Selection depends on the utility and execution time of the actions. The greater the benefit gained from the action of an agent, the higher will be the reaction rate and the shorter the reaction time (Loistl and Vetter, 2000). Attachment of time intervals to different actions and expected utilities results in time intervals of different length between two actions.

In (Shatner et al., 2000) traders do not make constant decisions: they ”sleep” and ”wake up” at times defined by previous decisions, that might concern pre-defined time, execution of an order, or reaction to some event.

Continuous sessions implemented in artificial markets represent mainly continuous automated order matching, where limit and market orders are matched against each other as they arrive, if possible, such as in a limit order book.

4.5 Execution systems

- Order-driven markets.

  Most of the artificial markets, such as the ABS in (Brock and Hommes, 1998), the SantaFe (LeBaron, 2002), the Genoa (Raberto et al., 2001; Cincotti et al., 2003), the business school in (Chen and Yeh, 2001), and the ASM in (Farmer, 2001) implement the auction type of execution mechanism. Traders submit simultaneously orders and those are centrally matched at a price that represents some kind of equilibrium.

  Besides call-auction type of markets, continuous-auction markets are represented in the literature. In most of the ASM’s that implement continuous trading sessions price formation is commonly based on automated central execution systems (Daniels et al., 2002;

Franci et al., 2001; Shatner et al., 2000, e.g.).

- Quote-driven markets.

  Although continuous dealer markets are very common (Reilly and Brown, 2003; Demarchi and Foucault, 2000), only very few studies try to conduct experiments in such kind of environments. We identified two of them by the literature survey. Artificial markets that represent continuous dealer trading are basically inspired from the microstructure literature. Accordingly, in (Das, 2003; Chan and Shelton, 2001) and (Loistl and Vetter, 2000) market makers set bid and ask quotes and execute orders, based on their beliefs (eventually position) and received orders.

  The most detailed, realistic representation of stock exchanges is implemented by the KapSyn model. Price formation in this model depends on the microstructure of the stock exchange that is modelled. In this sense the NASDAQ is represented as a dealer market, where trades are made at the dealers' quoted bid and ask price (Loistl and Vetter, 2000).

- Hybrid markets.

  Further, the XETRA market structure is represented in (Loistl and Vetter, 2000). Transactions in this ASM take place based on the content of the order book, that is at best bid or ask. Further, in special cases (e.g. open, close, extreme price change) auctions can be conducted. The market price determined by the auction is the quoted price at the highest trading volume.

4.6 Protocols

The protocols in ASM's are confined mainly to the possibility of short selling, or limit the size of the orders. At Santa Fe, for example the maximum number of shares that can be traded is 10, while it is possible to sell short up to 5 shares.

4.7 Transparency

Prices and dividends in ASM's are always made public without any delay. In case of quote-driven markets with continuous automated order execution mechanism, that is at the ASM's in (Chan and Shelton, 2001; Shatner et al., 2000) and (Daniels et al., 2002), the maximum bid and minimum ask quotes from the limit order book are public. AT KapSyn, if the XETRA model is selected, the content of the whole limit order book is available to all the participants during continuous trading sessions, and the best bid and ask quotes are published during call-auctions. Information reflects only price and volume and does not disclose the identity of the traders.

In addition several assumptions are made in the ASM's markets: publicly known forecast functions, agents who have perfect knowledge about market equilibrium equations, prices and fractions of belief types (e.g in the ABS introduced in (Brock and Hommes, 1998)). Although information of this type is not available on real markets, it makes artificial markets easier to be validated and as such the dynamics easier to be studied. Accordingly, results should be always analyzed in view of the assumptions.

5 Price formation and the behavioural factors in ASM's

In this section we consider the decision problems that traders, based on their role, face as identified in Section 3 and analyze how they are represented in the ASM's studied here. As illustrated by the "black-box" approach, the role and the outcome of the actions participants take (placed orders, transactions) are more or less visible on real markets, the details of the strategies, decisions, reasoning behind their actions are, however, not really observable by others. Designers, therefore, have to make a number of assumptions when they represent traders.

5.1 The order-placing behaviour

The way how various ASM's represent behavioural factors related to placing and determining orders is summarized in Table 2, based on the factors identified in Section 3 and is further elaborated in this subsection.

5.1.1 Policy statement

The main **investment objectives** of the modelled investors in ASM's is to get as much profit as possible (Chen et al., 2001; Farmer, 2001; Matassini and Franci, 2001, e.g.). In (Chen et al., 2001) they aim to achieve this through arbitrage opportunities. Investors in (Hommes, 2001) try to achieve a good performance by maximizing the mean-variance, while in (LeBaron, 2002; Chen and Yeh, 2001) and (Loistl and Vetter, 2000) they maximize some kind of utility function.

Further, traders aim to optimize their portfolio in (Raberto et al., 2001; Cincotti et al., 2003), to maximize wealth in (Shatner et al., 2000) and to achieve a personal gain with minimal loss in (Matassini and Franci, 2001). At KapSyn, where more assets are traded, participants have an individual benchmark portfolio in mind, which they want to achieve. Regarding the time-horizon the majority of the objectives can be said to be long-term as they hold during the length of the experiments.

The primary **investment constraint** that governs investments is implied by the finite amount of cash available to the traders.

Investors' **attitude to risk** is formulated in sense of risk averse traders. They strive to minimize loss in (Matassini and Franci, 2001) and minimization risk in (Shatner et al., 2000). Investors at Santa Fe ASM (LeBaron, 2002) and at the Business School with Genetic Programming (Chen and Yeh, 2001) are constant absolute risk-averse (CARA) utility maximizers of wealth, meaning that the risk they take is always a fixed percentage of their wealth. Further, at the KapSyn market in (Loistl and Vetter, 2000) risk is measured as the deviation of actual portfolio structure from the desired portfolio structure.

5.1.2 Investment strategy

Although it is not clear whether agents should evolve **forecasts of future prices** before making decisions or just evolve decisions directly (LeBaron, 2001), in the majority of the ASM's agents forecast before they place orders. In many ASM's traders take into account both fundamental and technical measures in order to forecast (Hommes, 2001; LeBaron, 2000; Loistl and Vetter, 2000, e.g.). At KapSyn, traders in fact, have a subjective price expectation in mind, that they think will be realized a the end of the planning period if necessary. The current price expectations of traders depend on this expected fundamental price influence and the influence of technical indicators, when traders think it is necessary. Additionally random traders are often considered (Daniels et al., 2002; Raberto et al., 2001; Das, 2003; Shatner et al., 2000; Chan and Shelton, 2001, e.g.). Random traders expect a random variation in the price related to the actual market price (Shatner et al., 2000, e.g.). Random traders can be actually looked as "bounded myopic" technicians. Expectations are often combined with random values to represent errors end bounded rationality in the forecasts of traders. At the Genoa market expectation is calculated based on current price and a random draw from a Gaussian distribution where standard deviation is dependent on historical volatility (Raberto et al., 2001). Random traders in this case are used to represent noise traders.

Fundamentalists or informed traders are represented in (Chen et al., 2001; Farmer, 2001; Brock and Hommes, 1998; Shatner et al., 2000; Chan and Shelton, 2001) and (Das, 2003), from which some traders in (Brock and Hommes, 1998) have a perfect foresight of the next market price, in the rest of the studies mentioned they know the fundamental value. Noisy information is sent to some agents in (Chen et al., 2001; Shatner et al., 2000) and (Das, 2003). At the Santa Fe ASM investors compare the dividend payed by the risky stock to the interest rate of the risk-free asset in order to have an indication of the fundamental value (Tesfatsion, 2004). Fundamentalists believe that the risky asset is over-valuated (under-valuated) if it pays more (less) than the risk-free asset. At the KapSyn market all the agents have individual expectations regarding the fundamental value of a stock.

The fundamental value of risky stocks, in the majority of the studies, is represented by a stochastic process, and as such, it follows a random walk in (Shatner et al., 2000) and a stochastic jump process in (Das, 2003), and alternatively, the logarithm of the value, follows a random walk in (Farmer, 2001) and a Wiener process in (Chen et al., 2001).

Next to fundamental measures, technical measures are considered by traders at Santa Fe Stock market when they make forecasts (LeBaron, 2002). All the traders apply moving average functions for the last few periods in order to try to guess in which direction will prices move to. Agents in (Chen et al., 2001) look at price trends as well, but they additionally might take into account the opinion of some other, more successful, participants. Besides trend followers, biased traders are focused in (Hommes, 2001), who just simply add or subtract a small number from current price. Further, several other technical trading strategies are applied, such as mean-variance, relative trading and mean-reversion in the Genoa market (Raberto et al., 2001; Cincotti et al., 2003), curve fitting in (Shatner et al., 2000), GP-trees for prices and dividends in (Chen and Yeh, 2001; Yeh, 2002) and up to 40 possible technical scenarios in (Loistl and Vetter, 2000). In (Matassini and Franci, 2001) a unique determination of the forecast value is given, where, besides the analysis of historical data, the opinion of other market participants, and the forecasts of the media is taken into account. Finally, traders search in a lookup table with historically successful strategies in (Franci et al., 2001).

5.1.3 Portfolio maintenance

Asset allocation. Since, most studies, expect to KapSyn, focus on the trading of one type of risky asset, the choice for the assets to included into the portfolio always regards that risky asset. The required weight of the stock usually depends on the utility function applied and at the Genoa market is determined as a percentage (drawn from a uniform distribution) of the owned shares (resp. cash), and the limit prices (Raberto et al., 2001). At KapSyn portfolios look more realistic, being composed by more stocks, in this case the required weight of each stock is again determined according to a utility function.

Orders. As described in Section 3.1.3, based on (Reilly and Brown, 2003), investors primarily place orders as part of a portfolio management process, and are entailed by the difference between required and current portfolio construction. This line of reasoning is applied at the Genoa stock market (Raberto et al., 2001; Cincotti et al., 2003) and in (Chen and Yeh, 2001; Yeh, 2002) to determine the size and side of the orders.

Most studies are, however, not concerned about the portfolio management problem, and determine the orders only in function of the future expectations of the traders. In (Brock and Hommes, 1998), for example, orders are similar to the forecast functions; on the Santa Fe market the **trading volume** is a demand function based on the traders' forecast in function of price and risk (Tesfatsion, 2004). Further, the number of shares required to trade is based on forecast and a fraction of wealth in (Matassini and Franci, 2001) and (Shatner et al., 2000). The traded quantity (resp. the invested cash)

The relation between the forecasted value and the market price can be used to determine the **trading side** of an order. In the most simple case traders decide to sell/buy if the expected price is below/above the current market price. In (Matassini and Franci, 2001) traders choose the trading side according to a so-called trading rectangle, which is based on historical analysis, objectives and constraints, and helps to decide whether stocks are over- or under-valuated. Further, stochastic functions are often applied to determine the trading side. Buy and sell orders are placed with equal probability in (Daniels et al., 2002; Shatner et al., 2000) and (Das, 2003). At KapSyn a probability of selection is linked to different utilities. Traders select the order they want to make stochastically based on some utility function and probability distribution (Loistl and Vetter, 2000). Further, the so called random traders, determine the trading side randomly.

Regarding the **quoted price** of the limit orders, in the literature the limit price defined by the traders is often the forecasted price of the stock. In reality however, traders do not submit their forecast values, but some deducted demand. In the CTAM described in (Shatner et al., 2000) this is taken into account.

5.1.4 Monitoring

Traders monitor the following types of data in ASM's, depending on the market organization where they interact: the new market prices, perceived fundamental values, bid and ask quotes if it is the case, and own and others performance. As conducted in Section 3 monitoring serves and entail **adaptation**.

In the ABS proposed by Brock and Hommes 1998; 2001 financial markets are modelled in form of nonlinear stochastic systems. In this model prices and beliefs co-evolve over time: the fraction of different agent-types changes based on the successfulness of the used strategy, such that in the next round, they will have a bigger influence on the prices. Similarly there is a transaction probability associated to the fraction of different types of traders in (Chen et al., 2001).

Other studies model investors' behaviour individually and although within an ASM the similar monitoring and adaptation strategy is used by the individual traders, the strategy of traders differs given the nature of the approaches applied. Next to simple changes, like to correct the expected value of a stock upward or downward, as it is solved in KapSyn, very often the whole set of strategies is adapted. There are two commonly used techniques to implement adaptive behaviour with regard to the set of strategies: neural networks and evolutionary algorithms, like genetic algorithms.

In (Chen and Yeh, 2001; Yeh, 2002) investors try to find the best trading strategies in so-called business school by means of genetic programming, where forecast functions are learned and adapted to the changing conditions. At the Santa Fe Artificial Stock Market, agents have individual sets of strategies, and genetic algorithms are used to evolve this set over time. Strategies are described by condition forecast rules, where the condition part contains market state indicators (fundamental and technical) and the forecast part contains the forecast parameters of the expectation function (trend, variance). Selection, mutation and crossover are applied to adapt the set of strategies to the changing conditions. The Santa Fe ASM is one of the first and most improved agent-based computational artificial markets, that follows the ACE approach and makes use of intelligent agents. Agents are processes implemented on a computer, that have autonomy (they control their own actions); social ability (they interact with other agents through some kind of protocol); and pro-activity (they are able to undertake goal-directed actions) (Weiß, 1995). Intelligent agents are able to incorporate the required behavioural issues, moreover, they are able to bring into effect learning and adaptive behaviour of the traders. That is necessary since the circumstances in which they interact continually change (price, news, goals) so they cannot use the same strategy if they want to be successful or even to survive. Evolution is the core dynamic at work of the agent-based markets both practically and philosophically (LeBaron, 2001). Agent-based computational economics (ACE) and micro-simulation approaches provide a means to model behavioural characteristics by considering traders as individual components, called agents.

A key-question in implementing evolutive behaviour is how to measure the ”fitness” of a strategy. A strategy can be said to perform good (given the market conditions) if it is the one, which provides the maximum return, wealth, utility, or the minimum forecast error among the other used strategies. Often, like for example at the Santa Fe ASM, the squared error of the forecast function related to the real outcome indicates the fitness of the forecast function. The performance of an investor depends further critically on the behaviour of other market participants (LeBaron, 2001). In the BS ASM described in (Chen and Yeh, 2001), for example, a ranking measure is provided, upon which traders can measure how good they perform related to the other participants.

5.1.5 Time factors

Let us take a look how the various dimensions of the time factor are represented:

- **time-horizon of the investment objectives:** investment objectives in the in the ASM's studied generally hold during the whole experiment.
- **forecast horizon of the investment strategies:** traders usually forecast one period ahead.
- **past horizon for historical data analysis:** the length of past time period for analysis varies a lot, theoretically any combination is possible. The maximum is 150 timesteps back, in technical rules using weighted averages, of course, even more data is included.

- **timing of order placement:** given the popularity of call-ASM's we can observe that the majority of the traders makes a trading decision and places orders every time-period. Additionally, the time moment for placing an order can be predefined or triggered by some event, such as news or price change, for the investors acting in the continuous market described in (Shatner et al., 2000). In the continuous session presented in (Daniels et al., 2002) and (Chan and Shelton, 2001) orders arrive based on a Poisson distribution, given that an aggregated representation of investors is applied. Further, a reaction rate is linked to each action in KapSyn. In (Matassini and Franci, 2001; Franci et al., 2001) traders decide based on a threshold and the situation of market state related to a so-called ”trading rectangle”.

- **waiting patience for the execution of an order:** in call-auctions where, trading of market order takes place every time period, and investors receive an answer immediately this factor is not relevant. However in markets where continuous sessions are represented and/or limit orders are placed, unexecuted orders can be cancelled after a while. The waiting time depends, for example, on the threshold in (Matassini and Franci, 2001), and is removed or cancelled stochastically in (Daniels et al., 2002).

- **time for monitoring changes and update:** traders usually analyze their performance from time to time and decide, mainly stochastically, based on a predefined threshold, linked to the fitness measure, whether to update their strategies. The analysis takes place at most of the ASM's every time, while for the agents at the Santa Fe ASM slow and medium learning periods of 100 and respectively 250 time periods are applied (Tesfatsion, 2004).

5.2 Execution of orders in ASM's

The various way orders are executed and as a result prices are formed on the ASM's studied is summarized in Table 3. We elaborate on the different execution mechanisms implemented in the rest of this section.

5.2.1 Brokers in ASM's

In stock markets orders initiated by investors are overtaken by brokers for further routing and execution (see: Section 3.2.1). Although several brokers interact on the market, with the well-defined role to execute orders on behalf of the investors, they are not represented in studies concerning ASM's. There is one single study that we have found, namely (Loistl and Vetter, 2000), which recognizes the importance to include brokers in ASM's, after designers consulted with financial analysts. The question is in which measure influences the introduction of brokers in various ASM's the market dynamics. We believe they have some influence as they might improve the price of the orders received, encourage trading and as a consequence provide liquidity and further, they might trade for own account as well.

5.2.2 Market makers in ASM's

The main role of the few market makers in the ASM's studied is to monitor the market through quoting bid and ask, and execute the orders received from investors. The position of market makers and their role to provide liquidity for inactive stocks is, however, rarely focused. The exception is the KapSyn market, where so called ”designated sponsors” interacting on the XETRA representation, can, but are not obliged to, set bid and ask quotes, to increase liquidity when there is only one order standing without any counter order. At other markets liquidity is provided in the sense that market makers are selling and buying for themselves. Further, at the ASM in (Farmer, 2001) the market maker trades based on his position. In this case, however, no special public bid and ask quotes are published, given that all the orders are market orders, and price is centrally set according to an automated mechanism.

Market makers, thus, need to match received orders against each other and determine **bid and ask quotes** that takes into account the content of the limit order book. A representative study that concerns market makers' behaviour regarding the determination of bid-ask spread is presented in (Das, 2003) and in (Chan and Shelton, 2001), where a multi-round Glosten-Milgrom model (see for a description for example (O'Hara, 2002) is implemented. In (Das, 2003) the market maker has a in fact a price discovery role, and sets the bid and ask quotes based on the received market orders and on the knowledge and assumption possessed regarding the fundamental value of the traded stock, and his assumption regarding the proportion of informed (who know what the fundamental price is) and uninformed traders. While the market maker in (Das, 2003) does not want to accumulate profit, the electronic market maker in (Chan and Shelton, 2001) sets its bid and ask quotes strives to maximize its profit given the order imbalance. The market makers at KapSyn modify their quote with respect to the limit order book, they cannot quote however, worse price than the limit orders in the book.

While in the studies described in (Das, 2003; Chan and Shelton, 2001) and (Loistl and Vetter, 2000) the market microstructure approach is used, most of the quote-driven ASM's apply mainly automated order matching mechanism and therefore we discuss them in the next section.

The **timing of the new quotes** is in all the studies entailed by the new orders arrived. In (Chan and Shelton, 2001) the electronic market maker, reacts when the order imbalance reaches a predefined threshold. Market makers, in general, do not have to change the quotes otherwise since, in the ASM's, they are not required to provide liquidity for non-active stocks, in fact the markets represented do not deal with inactive stocks, except for the XETRA.

Managing the limit order book At the XETRA representation in KapSyn market makers accumulate the unexecuted orders in limit order book. As orders of one size arrive one by one, and they are executed by definition there is no need for order book in (Das, 2003).

The transaction takes always place at the quoted bid/ask, and therefore the new market price is the quoted price of the matched bid or, respectively ask.

5.2.3 Automated execution of orders

Although a market maker is present, who acts based on his position in (Farmer, 2001), price is, in fact, determined centrally by an automated mechanism, based on the order imbalance, the position and risk aversion of market maker. Further, execution systems modelled in (Daniels et al., 2002; Matassini and Franci, 2001) and (Shatner et al., 2000) represent a **continuous automated order execution mechanism**, where new orders are matched against unexecuted orders that are stored and arranged based on price in a limit order book. Unexecuted limit orders are sorted (buy orders increasing, sell order descending), new market orders are executed immediately against the sorted book and limit orders are compared to earlier arrived, unexecuted orders in the book. If the quoted price of a sell order is lower than the price of a buy order transaction is made for the minimum of the quoted amounts. The market price is the quoted price of the order placed earlier, that is the quote. This price formation mechanism represents simple automated order matching but does not reflect more complex order clearance where market makers are involved.

Given that most ASM's implement order-driven call market sessions, they mainly have to decide how to define the **equilibrium price**. In the ABS introduced in (Brock and Hommes, 1998) market price is determined such that supply matches demand. In order to find the equilibrium point, this non-linear model assumes that the supply and demand functions of the traders are known by the order execution system. At Santa Fe, as well as during call auctions at the XETRA version of KapSyn, equilibrium is determined at the price at which trading volume is maximized (LeBaron, 2002). A new market price is often at the intersection of demand and supply curves (Raberto et al., 2001; Cincotti et al., 2003, e.g.), while in (Chen and Yeh, 2001) price is based on the excess demand/supply discounted with some adjustment value.

As illustrated by the large scale of design and implementation approaches applied in the ASM's studied here, there are arbitrary many ways to measure the fitness of a strategy, to implement adaptive behaviour, forecast strategies, construct portfolio and develop other decision strategies that lead the investors to place certain orders. The situation is the same with financial agents executing orders. And this is in fact what we expect, given the hidden feature of traders' behaviour on illustrated by Figure 3. The question is, however, how the implementation choices influence the traders' performance, and especially the market dynamics.

6 Discussion and future research

Analyzing the features of ASM's based on the overview presented above, reflected to the organizational and behavioural factors identified in Section 2 and Section 3 we can conclude that a common organization of most of the existing ASM's concerns:

- aggregated order-matching at discrete points in time,
- representations regarding participants who are centrally selected for trading and
- simultaneously make order-placing decisions.

The way orders are matched in these structures reflects call-auctions, but since most of the markets use (besides call-auctions) continuous trading, as observed in (Smith et al., 2002; Demarchi and Foucault, 2000) and (Reilly and Brown, 2003), they are not representative. Several studies consider only auction methods in artificial stock markets and set single market prices at some equilibrium by accumulating orders (Section 4). In (Hommes, 2001; Matassini and Franci, 2001) and (LeBaron, 2002) for example orders are aggregated and matched at single price and all the traders (or randomly selected groups of traders) simultaneously place orders. Prices might be set at equilibrium at call-auctions, most of the markets however allow for continuous trading. Further, aggregation might be indeed a useful tool for empirical analysis purposes, however it can be only used to study the dynamics of continuous markets if prices in the continuous market converge to the prices set by the call-auction. Equilibrium, however, does not necessarily occur on real markets where offers are placed and executed continuously (LeBaron, 2002). As noted in (Yeh, 2002), convergence to equilibrium is not guaranteed: market price is trading price in between certain pairs of sellers and buyers rather than an aggregate phenomenon induced by the market supply and demand.

Exceptions to the very common call-auction structure are in some measure the models described in (Loistl and Vetter, 2000; Smith et al., 2002) and (Shatner et al., 2000) where the need to study continuous trading is pointed out. These markets try to implement continuous order matching and even asynchronous decision making. An attempt at a continuous trading model is made in (Shatner et al., 2000) where traders do not make constant decisions but they ”sleep” after actions and ”wake up” at predefined times, or as a result of events. Other studies model continuity by randomly (Raberto et al., 2001) or stochastically (Loistl and Vetter, 2000) selecting one trader whose decision is carried out, and automatically matching new orders with pending ones if possible.

At the KapSyn, for example, all agents make decisions simultaneously at every (simulation) round, which is not the case in continuous markets. Moreover, the decision of only one agent is considered, the others are ignored and new decisions should be made, that consider the new market event. In this framework it can theoretically happen that some of the agents will never be selected to execute their actions. In reality all decisions are executed if possible, whether they were made simultaneously or not. Decisions are usually not made simultaneously, and do not wait for others' actions to be executed: someone can launch an action, before an event, triggered by an other agent, happens.

The problem with centrally and randomly selecting agents whose actions will be carried out, is that, in this way, agents are no longer autonomous regarding their actions and, as mentioned above, it might also happen that the decisions of some traders are not taken into account (Loistl and Vetter, 2000, e.g.). Representations of traders in ASM's illustrate passive agents, while agents on the market are autonomous and decide themselves whether they want their decision to be carried out or not. Autonomous behaviour can only be accomplished if the agents themselves decide when they want to trade as is the case in real markets.

As far as trader modelling is concerned, most ASM's focus on representing investor type of behaviour. There are no artificial stock markets to our knowledge that include brokers, and only a few markets with market makers (Das, 2003, e.g.), however their behaviour directly affects price formation. The need to represent market participants with different roles is pointed out in (Loistl and Vetter, 2000). Traders in literature are differentiated mainly based on their belief (expectation) regarding future values: fundamentalists believe that the price will achieve its real fundamental value, while technical analysts try to find patterns in historical data (Hommes, 2001; LeBaron, 2002; Loistl and Vetter, 2000, e.g.). Further, they usually determine their orders based on a function that maximizes their utility accompanied by a stochastic value or stochastic function (LeBaron, 2002; Loistl and Vetter, 2000, e.g.). Additionally, investors who trade randomly or according to some distribution function are seen as well (Shatner et al., 2000; Raberto et al., 2001, e.g.). Besides the strategies implemented in the ASM literature several others are described by empirical and behavioural studies, and many more exist in reality.

The vast number of trading strategies in a broad range of market organizations motivates us to design a framework that accommodates this diversity besides the unfocused microstructural features, such as continuous trading, asynchronous behaviour and autonomous behaviour, representation of brokers. Therefore, based on the list of critical factors and on the results (possibilities and shortcomings) of the analysis of current artificial stock markets we are developing a framework that provides a tool for representing several types of markets and an arbitrary number of trading strategies. Initial design details of the framework are described in (Boer and Kaymak, 2003).

We design traders as agents with different roles (investors, brokers and market makers) able to interact continuously and asynchronously. The few studies that consider in some measure continuous trading, try to solve for asynchronous behaviour from the programming level. In contrast we choose for a framework, where this is solved at a lower programming level (threads) and is proved to realistically represent continuity and concurrency (Boer et al., 2004a). By choosing for this environment we can focus on implementing traders' individual behaviour, that is a flexible combination of several specific and common sub-behaviours.

Besides implementing rarely studied market types and behaviours in order to study market dynamics, we aim to replicate, test and validate some of the existing artificial markets. Therefore, we strive for a reduced number of necessary assumptions during the design phase of the framework and configure different market structures and behavioural strategies on top of it (Boer et al., 2004b). We strive in this way to represent existing ASM's and as such to provide a tool for the validation and comparison of different market models. The introduced framework can help us, in this way, to study whether findings of experiments within different market models can globally explain some market dynamics or are the results of the chosen settings. Design details and experiments within the framework will be presented in a follow up paper.

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Structure \ ASM		CLM	Farmer	MDS	ABS	Genoa	MF	CTAM	SantaFe	BS	Das	EM	KapSyn
traded assets	**risk-free /cash**	-	-	-	1	1	1	1	1	1	-	1	1
	risky	1	1	1	1	N (2)	1	1	1	1	1	1	< 123
	fundamental v	log follows a Wiener process	logarithmic random walk	-	constant mean of the risky dividend / risk-free interest rate	-	-	random walk	relation price/dividend to risk-free interest rate	-	jumps with some probability	Poisson jump	individual constant expectation estimates
	dividend	-	-	-	stochastic IID	-	-	-	AR(1)	stochastic IID	-	-	-
orders	**limit**	-	-	X	-	X	X	X^{DF}	X	-	X^{MM}	X^{MM}	X
	market	X	X	X	X	-	X	-	-	X	X^{I}	X^{I}	-
participants	**investors**	N	N	N	N	N	N	N	25	500	N	N	< 123
	brokers	-	-	-	-	-	-	-	-	-	-	-	?
	market makers	1	1	-	-	-	-	-	1	-	1	1	N
trading session	**call**	X	X	-	X	X	-	-	X	X	-	-	X
	continuous	-	-	X	-	-	X	X	-	-	X	X	X
execution system	**order-driven**	X	X	X	X	X	-	X	X	X	-	-	X
	quote-driven	-	-	-	-	-	X	-	-	-	X	-	X
	hybrid	-	-	-	-	-	-	-	-	-	-	X	X

Legend for all the tables:
"-" factor is not represented
"X" factor is represented
"N" more than one issue represented
"number" number of given factors possible to use/used in experiments

"(*number)"* number of factors actually used in the presented experiments
^{DF} – price dependent demand function
^{MM} – orders posted by market makers
^{I} – orders posted by investors

Table 1: The organization of ASM's

Factors	ASM	CLM	Farmer	MDS	ABS	Genoa	MF	CTAM	SantaFe	BS	Das	EM	KapSyn
investment objectives		maximize profit from arbitrage	maximize profit	-	maximize profit	•optimize portfolio •provide liquidity	maximize profit, minimize loss, achieve gain	•maximize wealth •minimize risk	maximize CARA utility	maximize CARA utility	maximize profit by arbitrage	-	maximize utility
investment strategy	**fundamental**	• informed • noisy informed optimists/ pessimists	informed	-	informed with perfect foresight	-	-	noisy informed	expectation based on relation dividend, interest rate	-	• informed • noisy informed	informed	individual expectation optimists/ pessimists
	technical	opinion and price trend	X	-	• biased • trend follower	•mean-variance •relative •mean reversion	•trend follower •lookup-table	curve fitting	moving average	GP trees for historical prices and dividends	-	-	up to 40 scenarios
	random	-	-	X	-	liquidity	-	X	-	-	X	X	-
	other	-	seasonal	-	mixed	-	-	-	mixed	-	-	-	mixed
asset allocation/ orders	**size**	excess demand functions	fraction position	Poisson	forecasts functions are used	current-desired (portfolio fraction)	%wealth based on forecast	• random • %wealth	demand function based on risk aversion and forecast in function of price	current-desired	1	1	function return, risk, desired portfolio
	side		•position •seasonal	equal probability		sign size	trading rectangle	• random • arbitrage		sign size	• random • arbitrage	• rando m • arbitra ge	relation expected return, interest rate
	price	-	-	uniform probability (integer * tick size)		current discounted by random Gaussian	weighted • opinion • media • past	• random current ± tick		-	-	-	relation estimate, marginal market price
monitoring	**fitness**	transition prob. fraction traders	-	-	nonlinear dynamic: fraction of traders	-	- tuning real data - lookup table best strategies	- change in waking parameters	GA: forecasting rules based on forecast variance	GP: forecast price and dividend	-	-	- change in expectation - utility of actions after evaluation
timing	**past**	1	N	-	N	10-150?	1-150	N (3)	50/100/150	N(10)	N	1/2/3	N
	order	Poisson	1 sync	Poisson	1 sync	1 sync	1 / threshold	**predefined/ event based**	1 sync	1 sync	1 stochastic	Poisson	1 simulation time
	monitoring fitness				1				• 100 • 250	1 - 20			

Table 2: The order placing behaviour of investors in ASM's

Type \ ASM	CLM	Farmer	MDS	ABS	Genoa	MF	CTAM	SantaFe	BS	Das	EM	KapSyn
call-auction	stochastic Walrasian: stochastic change by small increase / decrease (0.001)	based on imbalance risk, and position	-	supply = demand	intersection supply-demand	-	-	supply = demand and does not exceed available number of shares	based on excess demand and speed of adjustment	-	-	highest volume
continuous automated	-	-	bid/ask from the order book	-	-	match sell/buy in the order book	earliest best matching bid/ask in the order book	-	-	-	-	-
continuous quote	-	-	-	-	-	-	-	-	-	quoted bid/ask based on Bayesian learning	quoted bid/ask based on position, imbalance and threshold	quoted bid/ask based on content order book

Table 3: Order execution mechanisms in ASM's

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