Contributions to Adaptable Agent Societies

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***Abstract* - The adoption of agents as utile companions faces the problem of conciliating the development of complex and intelligent functionalities with the requirements of autonomy mobility and adaptability. Our main focus will be on the agents adaptability. A hybrid agent architecture approach is proposed where a static component, which resides at user's host and includes most of the intelligence and decision support capabilities, is complemented by a mobile component that is aimed at interacting with other agents. Some adaptation strategies, based on classical and fuzzy methodologies, are also discussed using as background scenario a trading market competitive environment with buyer and seller agents interacting in it.**

I. INTRODUCTION

In this paper we present a trading system example, using a hybrid approach architecture, to test and discuss the subject of agent's adaptability. The main goals for the trading system prototype are:

- Agents act on behalf of users and try to satisfy both their needs and preferences;
- Agents acting as buyers learn users' preferences by taking into account either the selections made by them during the procurement phase of trade (if working in a non-autonomous mode) or based on some feedback about the adequacy of buys already done (if working in autonomous mode);
- Agents need to adapt to the market environment. This means that the agents require a Knowledge Base to be built, kept available and updated in order that all of them work in a consistent way;
- Users may provide its agents a list of products to buy and/or launch several buying processes within a short period.

The main assumptions for our system are that:

- the market may be widely spread over the Universe;
- there are time and communication costs involved;
- the infrastructure may be affected by failures; and
- there's convenience to satisfy some performance requirements like, for instance, mobility (and communication costs); time to perform tasks; knowledge survivability; and/or behaviour consistency.

Considering the need for accommodating decision support functionalities for the agent adaptability study we considered a hybrid agent architecture approach that includes: i) one user host resident or "fat" agent (the static agent); and ii) a variable number of mobile "slim" agents that explore the market, interacting with other agents in different host locations (the mobile agent), to retrieve data.

The static agent centralizes the knowledge collection and dialogues with the user, acting like a decision support system or expert system, according to the degree of autonomy granted by the user. This agent acts also as a mobile agent dispatcher, assigning tasks to the mobile agents. The mobile agents may be launched with different characteristics, allowing them to evolve by means of a best-fit selection process.

Static agents can act as buyers or sellers and, eventually, both as buyers and sellers.

Thus, the features of the proposed hybrid approach, consisting of one static agent (Local to user host) and n mobile agents, are:

Static agent (includes decision-making support / expert system features [1]):

- Interfaces with the user receiving requests to buy and/or sell goods;
- When buying:
  - o Launches mobile agents to search the market space (procurement activities);
  - o Collects mobile agents data, evaluates the degree of fitness/satisfaction regarding user known preferences and selects/sorts the best rated offers;
  - o If working in a non-autonomous mode, proposes to the user a ranked list of products located in the market space;
  - o If working in an autonomous mode, buys/negotiates the product price, on behalf of the user, according to the ranked list of product offers.
- When selling:
  - o Evaluates market trends and fixes a profit value;
  - o Negotiates available goods price/features on behalf of user.

Mobile agents:

- Search the market space (procurement activities) locating seller agents and retrieving information about market goods that fit users requirements and/or have some degree of communality with such requirements;
- Buy goods on users behalf;
- Perform marketing activities of products in stock.

Naturally the goals of buyers and sellers are antagonistic. Usually sellers want to maximize the Profit/Trade Volume ratio (over time), while buyers want to ensure survivability and maximal satisfaction at minimum cost.

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To achieve such goals we consider different strategies, which is somewhat similar to having different forms of adaptation. For instance, **sellers** can act on factors like: (a) Profit (adjusting profit to demand level); (b) Product Stocks (variation of type and/or quantity of items in stock); (c) Selection of Location (move to a more favourable site), and **buyers** can vary their (a) Preferences (what user likes and/or the requirements of products to purchase); (b) Location; (c) Buying frequency of non-essential goods.

It is common knowledge that markets react according to a supply and demand law. In periods of high demand sellers increase prices; on the other hand if supply is high they decrease prices. Buyers make business trade depending on their own wealth, and by managing their activity according to some cost/benefit analysis. In this sense benefits can be used to measure the satisfaction a product offers, which in many cases is a subjective perception. Consider, for instance, the choice of the colour of a car. While a senior executive wouldn't be vary happy with a pink car, a young graduate girl eventually would.

In order to evaluate the performance of trader agents and to select the best trend of an offspring evolution, we need some measures of agent performance. Seller performance can be evaluated by means of the average profit, generally computed as:

Average Profit = (Sells – Expenses) / Time

where:

Expenses = Producer Price + Distance Cost + Selling Costs (agent existence)

Buyer performance may be evaluated by means of a ratio combining the degree of satisfaction of user requirements with the costs involved with its purchasing:

Cumulative Satisfaction / Expenses (buying costs)

where:

Cost = Price + Distance Cost + Procurement Costs (agent existence)

Both performance measures need to be maximized.

The current paper will focus on the static agent internal model of the Hybrid architecture and some alternative adaptation strategies, based on classical and fuzzy [2] approaches. Another paper by the authors [3] is a complementary paper to the present one, where we address mobile agent model aspects and discuss matters related with agent's evolution by the adoption of an Artificial Immune Systems approach [4].

II. HYBRID SYSTEM CHARACTERISTICS

The general characteristics of the hybrid system are:

- Users wanting to buy/sell products own local (static) agents that act both as procurement agencies/sellers and decision support systems;
- Static agents act as adaptative decision support systems, which advise the users, and have the ability to adjust to market modifications;
- When buying, static agents are capable of evaluating procurement results, selecting and ranking the deals which are more adequate to user requirements;
- When selling, static agents are capable of evaluating selling trend and adjust profit to ensure best ratio profit/sell volume (average value over time);
- Static agents can dispatch mobile agents that search the space looking for (or offering/promoting/ announcing) goods (Fig. 1);
- Product type and other features are identified based in some ontology, which characterizes the product in order to allow the evaluation of the matching degree with specific demand requirements;

The characteristics of the Buying process are:

- The static agent (at users host) receives user's requests and launches mobile procurement agents that search the network space looking for adequate sellers;
- mobile agents report their findings to the static agent;
- static agents can evaluate supply offers based on demand requirements, together with factors like object cost (seller price + delivery costs) and delivery time;
- The selection of the best deal is done after some data retrieval time limit. If the evaluation of some product offer rises above some acceptability threshold, the procurement phase may be terminated and the deal proceeds without further delay;

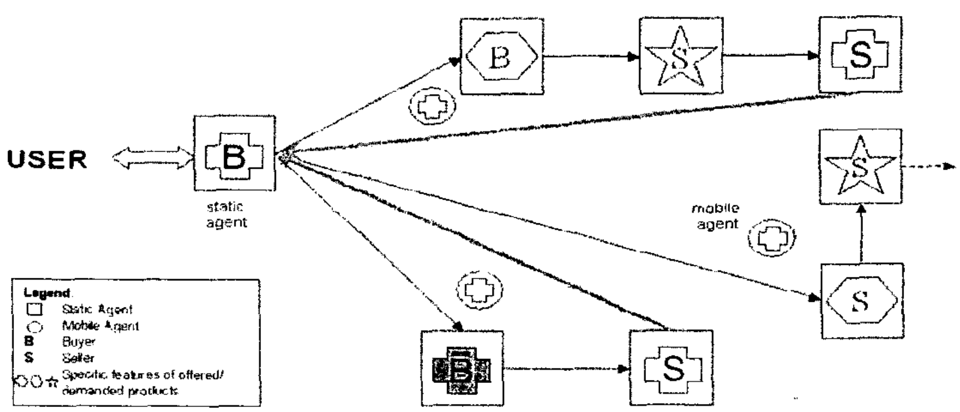

Fig. 1 – In the hybrid system static agents dispatch mobile agents that look for products with certain specific features

- The evaluation of product characteristics, based on user preferences, produces a real number in the interval [0, 1]. Each parameter is evaluated individually based in a function (e.g. a ratio) that also produces results in the interval [0, 1]. The importance of each evaluation parameter is weighted by means of a real number. The sum of all weights equals one. In this way the evaluation of a product is done using an weighted average;
- After the end of the procurement phase, to move immediately with the deal will depend on the autonomy granted by the user. If the agent is autonomous the purchase proceeds. Otherwise the static agent provides the user with search results (sorted according with current knowledge) and waits for a user final decision;
- A commitment with the best dealer available is tried, following the sequence of a list of sorted alternatives, whose results were rated above some threshold level.
- A static agent adjusts the preference weights for product features based on the selections of user, when it operates in non-autonomous mode, or by means of some feedback provided by the user about deals performed in autonomous mode.

The main characteristics of the Selling process are:

- mobile agents may settle in "market nodes" promoting the sell of user's goods;
- mobile agents may have negotiation capabilities;
- mobile agents report results to static agent and wait for a commit/discard order;
- static agents can sell directly products to a third party mobile agent wanting to buy products from user's stock.

III. HYBRID SYSTEM MODEL

As previously mentioned the Static Agent acts like a Decision Support System, assisting the user trading activities. In order to ensure such capabilities the Static Agent has to interface both with the User and the Cyber World; it has to maintain a Knowledge Base; it has to keep track on current deals; and it has to possess sufficient reasoning abilities to evaluate and select/rank trading opportunities. On the other hand the Static Agent must have adaptation characteristics that allow the adjustment to user's new demands and/or preferences as well as to trading market evolutions. These characteristics are provided both by means of adaptation rules defined in the Knowledge Base and by Immune Systems features, related with the generation of Mobile Agents and with the Product Matching functionalities that checks if the required demand vs. offer commonality is present. The particulars regarding the mentioned Immune Systems features are discussed in a separate paper [3].

Fig. 2 presents the internal model of the static agent of the proposed Hybrid-Agent approach, where the components that ensure the referred capabilities are shown.

During the current study we will focus on the core of the agent and leave out the discussion about the characteristics of which ontology to use in the ecosystem and about the Immune Systems component.

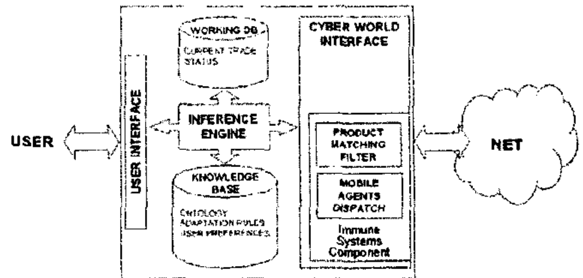

Fig. 2 – Hybrid Agent model – the static agent

A. Trading Phases

In this market model two phases for each deal are considered, one corresponds to the *procurement* and the other to *negotiation*. In the procurement phase mobile agents retrieve information about selling offers, and return it to the static agent to be evaluated. During the negotiation phase the buyer tries to achieve a better deal, mainly by reducing the price. Eventually the negotiation may involve other product features, in order to get a product more fitted to user's preferences.

The static agent that initiates a product demand can define the duration of each of these phases. For instance, if the buyer knows the market quite well it can reduce drastically the procurement phase, since it knows where to find a product and, eventually, the offer prices. On the other hand, if the product buy is urgent the buyer can reduce or eliminate the negotiation phase.

Between these two phases the static agent has to complete the evaluation of offers and, depending on its autonomy level, it can proceed with the deal (in autonomous mode) or provides the user with a ranked list of alternatives and waits for his feedback (in non-autonomous mode).

Mobile agents stop the search for product sellers returning any available information when the procurement phase expires. Considering the return of information, the mobile agent can keep on searching for selling offers until the procurement phase ends, providing the static agent with the retrieved information only at the end of the procurement phase or it may send the information as soon as it gets some. The first approach has the chance to better explore the market, however requires mobile agents with higher memory capacity and can lead to a traffic jam in the static agent at the end of the procurement phase. The second approach allows the distribution of the evaluation process along the procurement phase and allows immediate detection of acceptable deals that could proceed to the following deal steps, shortening the trading process in case of urgency. Eventually the mobile agent can proceed with the market search after passing the information to the static agent.

The mobile agents may, eventually, collect information about other products found that allow the building of a reference catalogue in the static agent. Alternatively sellers may promote their own products, providing information to buyers that allow them to get acquainted with available products and respective features (build up its own ontology knowledge base). Both strategies are possible; its adoption depends on an active or passive behaviour the agents choose to adopt in the retrieval/diffusion of information within the trading system.

The eligibility of offers depends on the achievement of a minimum acceptability degree. Offers bellow that level will not be considered as acceptable deals.

B. Buyer Evaluation Process and Adaptation

For the evaluation process we assume to have an ontology that characterizes a product based on n features (standard at product level). One mobile agent, which is performing procurement, has to collect data about the particular features of market available products, as well as price and available quantity per seller found. Relative to the eligible sellers the mobile agent has to get data about identity (host + agentID +...) and respective "world coordinates" or equivalent information. The coordinates "geographical" information is necessary in order to estimate distance costs and/or delivery time, thus avoiding buys that are unfeasible due to distance between traders.

When evaluating several product offers, the static agent has to consider the current knowledge about the preferences of the user. Users may establish these preferences when they ask agents to look for some specific products (including explicit features) or, alternatively, they can adopt/rely on agent known preferences, resulting from previous procurement activities related with the same type of products. The static agent has to build a Knowledge Base where it stores, for instance, data about the market (products ontology, sellers products/location) and user's preferences.

When evaluating the received offers, concerning some current product demand, the agent has to consider some features mandatory (at least the product must coincide in type with the requirements defined) while others may be flexible (e.g. price, colour, ...).

If a product doesn't satisfy a mandatory feature it is excluded.

Acceptable products are rated and ranked according with a classification, which depends on the degree of fitness/satisfaction of the product regarding the user's preferences and with the respective importance of the features.

Each feature requires a particular evaluation function. The evaluation can use continuous functions, in case of numerical data, or discrete functions, when feature data is based on an enumeration of alternatives.

Lets first consider the continuous evaluation functions. For this purpose we will use fuzzy membership functions [2]. Depending on the feature to evaluate, different shape functions can be adopted, for instance triangular, trapezoidal or Gaussians. . The membership function' x-axis represents quantitative values like, for instance, price, distance or age. The y-axis represents a quantitative continuous degree of membership in the interval [0, 1] in which some x value fits the concept that the function expresses, for instance "*acceptable price*". A y value equal to 0 means that the element does not belong in the evaluated concept, 1 means that it totally "matches" the evaluated concept, and an intermediate value means a partial fit.

Lets consider the use of continuous functions in the evaluation of price. The user has to define some limits for the amount of money he accepts to pay for the product. We can assume that these limits are two, a *fair price* and the *top price*. Any price below the *fair price* is totally acceptable. Prices above the *fair price* tending to the *top price* will have a decreasing acceptability degree. Products with prices above the *top price* will be excluded. This evaluation can be performed by means of a continuous Z function, like the one shown in fig. 3.

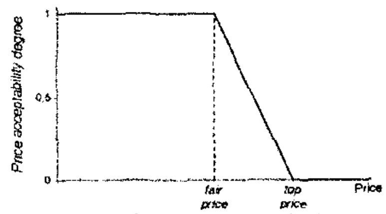

Fig. 3 – Z function for price evaluation

Examples of the use of continuous functions with other shapes include:

- S functions can be used to evaluate features where the references are set on the left side, e.g., buying something bigger that some minimum value, and preferably above some specific measure;
- trapezoidal functions are adequate for evaluations limited on both sides, e.g. look for cars with engines within a certain range of litres.

As previously mentioned the results of the evaluation functions are numbers in the interval [0, 1]. 0 means not acceptable, 1 totally acceptable and values in between means partially acceptable feature.

Discrete type features will be defined as linguistic variables [5], where each term relates with a value that represents its acceptability degree.

Lets consider, for instance, the evaluation of a car colour:

- colours found completely unacceptable are associated with an acceptability degree of 0;
- preferred colours are assigned an acceptability degree of 1;
- different colours will receive increasing values above 0 according with the degree of acceptability they have.

Fig. 4 illustrates this kind of evaluation functions, considering the car colour feature eventually adopted by an executive whose preference goes to a green car. The definition of the linguistic variables is done by means of a set of pairs that relate the linguistic term with its respective membership degree.

Considering the car colour evaluation example illustrated on Fig. 4, the *acceptability* linguistic variable would be defined as follows:

Car colour acceptability = {(magenta,0), (cyan,0), (yellow,0.2), (orange,0.3), (red,0.4), (white,0.7), (black,0.7), (blue,0.9), (green,1)}

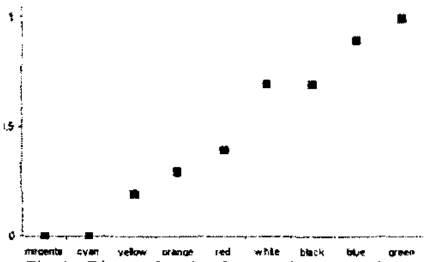

Fig. 4 – Discrete function for car colour evaluation

For the global evaluation of a product each feature individual evaluation is weighted based on the importance the user has assigned to it. The final rating of a particular product is calculated using a weighted average [6], defined as:

$$r_i = \frac{\sum_{1}^{n} w_{ij} \cdot a_{ij}}{\sum_{1}^{n} w_{ij}}$$

where:

r_i – rating of product i

w_{ij} – weight (importance degree) of j feature of product i

a_{ij} – acceptability degree of j feature of product i

n – total number of features

Considering the knowledge representation for continuous evaluation functions definition we propose the approach used in [7], consisting of dynamic parametric fuzzy functions. The basic parametric definition of continuous fuzzy membership functions is based on four parameters used to define the contour of the curve, for instance Z, S and trapezoidal and one parameter to define if the curve type is linear or quadratic.

The dynamic characteristics of this parametric function definition may be useful if a constraint relaxation strategy is followed. For that matter a new parameter is considered that controls the degree of relaxation to introduce. For instance buyers *top price* may slide after some time if no deal offer is found. In this case a re-evaluation of excluded offers may lead to a feasible deal. Fig. 5 illustrates this situation.

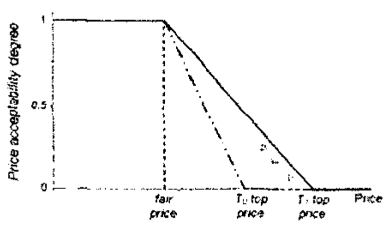

Fig. 5 – Relaxation of evaluation constraints using of dynamic functions

This is one of the ways defined for the buyers' adaptation to the market. In this case a buyer that doesn't find a product that fits initial constraints may try to broaden the acceptability spectrum in order to absorb previously excluded alternatives. This is particularly useful when none of the offers satisfy a particular feature.

For this purpose, after some defined time (T_0), parameters *top price* will tend to get apart from *fair price* following a generic rule like:

$$\begin{aligned} &\textit{top price}\ (t) = \textit{fair price}(t_0) + \\ &+ \alpha(t) \cdot [\textit{top price}\ (t_0) - \textit{fair price}(t_0)] \end{aligned}$$

where *top price* (t) are the new curve parameters; *fair price*(t_0), *top price* (t_0) are the reference curve parameters; and $\alpha(t)$ is coefficient with a value equal or greater than 1.

The $\alpha(t)$ coefficient can be, for instance, given by the generic function:

$$\alpha(t) = \begin{cases} 1 & t \le T_0 \\ 1 + m(t - T_0) & t > T \end{cases}$$

where:

T_0 - time delay after which constraint relaxation starts

m - line gradient ($m > 1$)

How much $\alpha(t)$ grows depends on the relation between the instants T_0 and *end of procurement*, and also on the variation gradient.

A different way of adaptation is to give preferences different weights. In this case the evaluation focus is shifted to other product features.

C. Seller behaviour and adaptation

Any static agent can be addressed by other agents that are looking for specific products. If the static agent has products to sell it will answer with the price, quantity and complete characteristics of available products that may fit the requirements of the buyer.

A static agent addressed by another agent, which is trying to complete a deal, must first check if the required product is still available.

Considering the adaptation to the market, sellers may react to the market demands varying the price of available products or adjusting the stocks of products with particular features, increasing or decreasing them.

Lets consider the sellers adaptability by means of price adjustment. Sellers may establish a desirable product-selling rate, adjusted to the reference average profit earlier mentioned. This gives a measure of the sells flow.

A flow too low means either that there is no demand for the product or that the offer price is too high. In either case the strategy to increase the sells is to decrease the offer price. The price variation can be more or less abrupt depending on how far the seller is from its selling rate goal.

A flow too high means either that there is high demand for the product or that the offer price is too low. In either case the correct strategy is to increase profit, i.e., to increase the offer price. Then again the price variation can be more or less abrupt depending on how far the seller is from its selling rate goal.

Fig. 6 illustrates such concept.

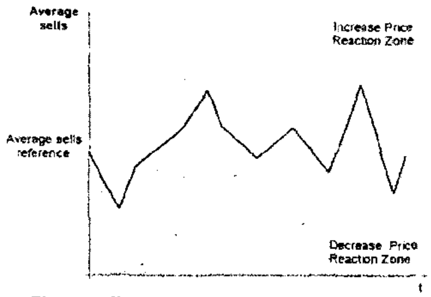

Fig. 6 – Sellers' reaction according to trading flow

In the current model we assume that the profit variation is kept between some minimum and maximum values. Thus the reduction of price, when the trade flow is low, is achieved using a function that makes the profit margin tend to the minimum value. On the other hand, when the trade flow is high, the price increase is achieved using a function that makes the profit margin tend to the maximum value. Those functions may follow different laws, corresponding to different strategies. Fig. 7 illustrates exponential and linear curves, corresponding to price (profit) variations that may be more aggressive or more prudent, depending on the higher or lower initial curve gradient.

For this purpose a general conceptual algorithm can be considered that, depending on product sells data (like current profit and average sells) and on some reference data (like maximum profit, minimum profit and average sells reference), provides a trend to follow on price adjustment. Further, the curve contour can also be parameterised by means of two parameters: a time constant (τ), which defines how long it takes for profit to reach the maximum or minimum level; and a constant (k), which controls the transition from a prudent to an aggressive variation.

Thus, considering:

p_{max} – maximum profit	s_{av} – average sells
p_{min} – minimum profit	s_{ref} – reference average sells
$p(t_0)$ – current profit	τ – time constant
	k – constant

a ratio (δ) between the average sells (s_{av}) and the reference average sells (s_{ref}) is calculated, according to the formula:

$$\delta = s_{av} / s_{ref} \qquad \forall\ s_{av} \text{ and } s_{ref} > 0$$

The increase, decrease or maintain trend for profit depends on this ratio being greater, smaller or equal to 1. The following expressions reflects the approach we used :

$$p(t) = \begin{cases} p(t_0) + (p_{\max} - p(t_0)) \cdot \left(\dfrac{t - t_0}{\tau}\right)^{k\delta} & ,if \quad \delta > 1 \\ p(t_0) & ,if \quad \delta = 1 \\ p(t_0) - (p(t_0) - p_{\min}) \cdot \left(\dfrac{t - t_0}{\tau}\right)^{\frac{k}{\delta}} & ,if \quad \delta < 1 \end{cases}$$

Fig. 7 illustrates the results of this algorithm for different values of the δ ratio. The k constant adopted in graph generation was $k = 2$. Higher values of k will lead to a more prudent variation trend while lower values of k will lead to a more aggressive variation trend.

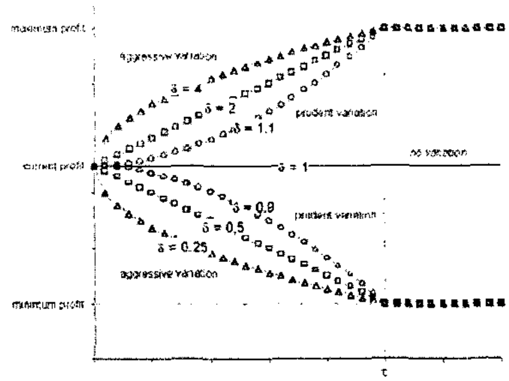

Fig. 7 – Profit adaptation algorithm (k = 2)

Other profit adaptation strategies can be followed using, for instance, formulations like sigmoid shape profit adaptation curves, linear curves or stepped adaptation curves. For our studies we defined 5 types of strategies considering different price adjustments formulations. Table I summarizes the 5 strategies considered.

Since we consider that in a competitive market environment the more interesting adjustment situations are the ones related with low trade flow ($\delta < 1$) we focused on price adjustment strategies aiming this particular situation. The five strategies considered are presented at Table I and the new ones are illustrated on Fig. 8.

Table I – Some alternative strategies for sellers' profit adjustment on low trade situations

Strategy Name	Formulation [for $\delta < 1$]	Description
static	$p(t) = p(t_0)$	No adaptation exists
Parametric	$p(t) = p(t_0) - (p(t_0) - p_{\min}) \cdot \left(\dfrac{t - t_0}{\tau}\right)^{\frac{k}{\delta}}$	Described above (see fig. 7)
Stepped Linear	$p(t) = p(t_0) - (p(t_0) - p_{\min}) \cdot (1 - \delta) \cdot \left(\dfrac{t - t_0}{\tau}\right)$	Profit depends on distance to trade objective varying linearly (see fig. 8.a)
Stepped Power	$p(t) = p(t_0) - (p(t_0) - p_{\min}) \cdot (1 - \delta) \cdot \left(\dfrac{t - t_0}{\tau}\right)^{k}$	Profit depends on distance to trade objective being aggressive or prudent based on k parameter (see fig. 8.b)
Stepped Sigmoid	$p(t) = p(t_0) - (p(t_0) - p_{\min}) \cdot (1 - \delta) \cdot \frac{1}{2}\left(1 - \cos\left(\dfrac{t - t_0}{\tau} \cdot \pi\right)\right)$	Profit depends on distance to trade objective. Initial variation is prudent becoming aggressive latter (see fig. 8.c)

A different type of adaptation a seller may present (not based on profit adjustment) is to offer products with features that have been demanded by buyers or, eventually, with completely new feature characteristics. Such approaches correspond, in the first case, to adjust the supply to the demand and, in the second case, to innovation.

For the adaptation based on adjusting the supply to the demand it's just a matter of memory, i.e., it is possible to detect new demand trends if sellers keep some history of product features that were lately asked for.

For the adaptation based on innovation sellers may try to add new alternatives to the existent features and evaluate the commercial success of such modifications.

Static agents, acting as sellers, can also promote their products by launching mobile agents that provide information to other agents about available products. Although this kind of promotions can provide the competitors with "no cost" tools for adjusting its own offer, it may be the only way of incorporating innovation and of automatically evolving with the ontology that is in the foundation of the trading system.

IV. HYBRID SYSTEM SIMULATION

The seller adaptation behaviour was studied in terms of model parameters effect, for isolated agents and under a competitive environment.

Initially we run tests with just one seller, which is dealing with one product in a market where n buyers existed with different degrees of product acceptability (in the example $n = 30$). The tests were run during a certain number of time units where buyers query the seller about the product price and decide whether it is acceptable or not. During the tests different buyers access the seller at each time unit, in a random sequence. Each buyer has his own price evaluation criterion. The product has a reference price to which is added the seller profit. For the product price contributes also a distance cost that is defined per buyer.

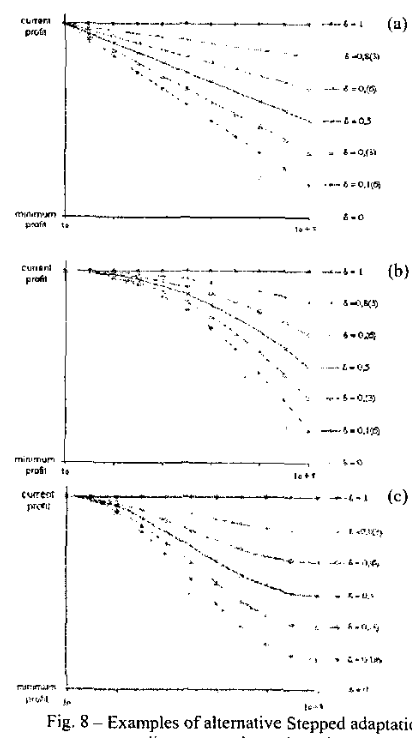

Fig. 8 – Examples of alternative Stepped adaptation Sigmoid, corresponding to a prudent adaptation at the beginning and a more aggressive adaptation at the end

The seller tries to adjust its profits so that product trade flows approximately at a desired rate (see Fig. 9). For the performed tests, the reference trading flow rate was set to 3/5, meaning selling 3 product items each 5 time units.

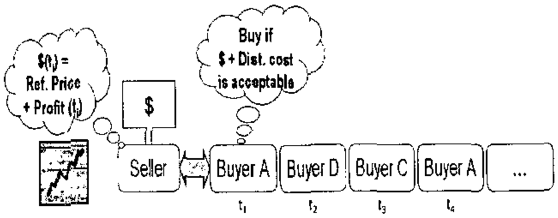

Fig. 9– The seller tries to make prices acceptable to buyers' population by adjusting the profit according to deals performed along the time

Product reference price and buyer evaluation functions were defined so that the final price would cost around 1000. Buyers' acceptability functions were set individually so that some are willing to pay more than others. There are buyers with identical acceptability functions but their distance to the seller varies, which may affect the final decision since the total price depends on buyer-seller distance.

The seller evaluates the number of articles sold during the last τ time units (i.e., an observation window or a memory) and checks if profit adjustment is required, and the direction and intensity of the adjustment. During the tests the effect of changing the window sizes was observed. Another aspect verified was the adaptation effect when different degrees of aggressiveness/prudence behaviour are simulated (by controlling the k parameter) and when different reference prices are used. Tests were also performed where low performance agents were killed and new ones were generated on its place. The latter tests involved also the study of dynamic profit margin limits. In summary, the tests performed took into consideration the following scenarios:

- Variation of the test run duration;
- Variation of the observation window duration (τ);
- Variation of the reaction behaviour (k);
- Variation of the reference price;
- Variation of the seller survival conditions.

In order to observe the behaviour of sellers in a competitive environment, a new set of test runs were performed involving several sellers that compete among each other, trying to sell the same product. Each seller acts in the previously described way. However, since buyers have more available sources, now they not only decide if but also where to buy the products they demand. Fig. 9 illustrates the behaviour of sellers using different price adjustment strategies in a competitive market environment. The lines represent the profit applied to the price.

In summary the scenarios defined for testing a seller adaptation in a competitive environment were:

- Identical conditions for each seller;
- Variation of the reference prices;
- Variation of the distances to buyers;
- Variation of the k and parameter;
- Variation of the adaptation strategies.

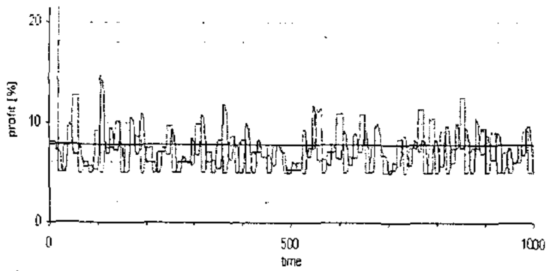

Fig 9 – Example of a test run to study the profit adjustment behaviour of 3 seller agents trading on a competitive environment. The agents use different strategies, one uses fixed profit (horizontal dark line) and the other two use price adjustment strategies (dynamic lines)

In order to perform the above-mentioned tests a specific Demonstrator application was developed in Java.

V. CONCLUSIONS

We developed an adaptive agent model suitable for a traditional buyer/seller market scenario. We took in consideration that buyer and seller goals are not common so the adaptation model is role dependent. However the agents are fit for playing both roles and have interaction functions that are role independent. For each of these two roles, a specific adaptation algorithm was developed that allows an agent to achieve better deals in selling and/or buying. Sellers seek to maximise the profit they obtain on trades, and buyers want to maximise the acceptability degree of the goods they buy, affected by some price or user preference constraints. Since agent mobility and agent intelligence are inversely related features we adopted a hybrid agent architecture where each agent comprehends a static intelligent and persistent component (static agent) and mobile dumb and volatile components (mobile agents). Sellers and buyers interact with each other through mobile agents. Sellers and buyers are static agents that don't move from their home host. They interface with the user and can act as decision-support systems or decision makers, depending on the granted autonomy degree. Decisions are based on information generated by mobile agents that they create. Mobile agents collect information about the agent system and perform trading on behalf of their owner static agents.

In general, our strategy was to create static and mobile agents, related with a design strategy in which computing and resource-demanding agents stay fixed on a network node, while light agents work as information disseminators (delivering and collecting it). For the information representation and for the adaptation algorithms definition we used both classical and fuzzy methodologies. The classical approach was adopted mainly in the seller's reactive adaptation model while the fuzzy approach was used basically in the buyer's decision model.

The developed model proved to be effective in a competitive trading environment, since agents adapt quite successfully to market conditions having better performance than non-adaptive agents.

Despite the fact the proposed adaptation algorithms are task specific, the basic model is applicable to many real world situations. The buyer adaptation model is applicable, for instance, to Multi-Attribute Decision Making problems where different alternatives are rated and ranked based on some evaluation criteria involving preferences or importance degrees [6, 8]. The seller adaptation model is an example of control problems where the feedback from previous states can affect future outputs.

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