We are IntechOpen, the world's leading publisher of Open Access books
Built by scientists, for scientists

6,900
Open access books available

186,000
International authors and editors

200M
Downloads

154
Countries delivered to

Our authors are among the
TOP 1%
most cited scientists

12.2%
Contributors from top 500 universities

CLARIVATE ANALYTICS
BOOK CITATION INDEX
INDEXED

WEB OF SCIENCE™

Selection of our books indexed in the Book Citation Index in Web of Science™ Core Collection (BKCI)

Interested in publishing with us?
Contact book.department@intechopen.com

Numbers displayed above are based on latest data collected.
For more information visit www.intechopen.com

Negotiation in Multi-Agent Environments

Dorin Militaru
Amiens School of Management
France

1. Introduction

Internet offers many choices of products, services and content. But the multitude of choices has altered the manner in which customers choose and buy products and services. Internet searching agents are tools allowing consumers to compare on-line Web-stores' prices for a product. In the field of electronic commerce, consumers can already benefit from the use of searching agents that automatically query on-line sellers' catalogues in order to gather information about available products. These agents have different degrees of sophistication and differ in their ability to process information. Intelligent agents in artificial intelligence are closely related to agents in economics. They can adapt to the needs of different users, it can learn new concepts and techniques, it can anticipate the needs of the user, and it can take initiative and make suggestions to the user. Negotiation is an important mechanism for resolving conflicts between individual or economic agents. Intelligent agents can provide services in filtering data, searching for information, online tutoring, and negotiation.
In this chapter, we present a study that investigates how costly information could affect the performance of several types of searching agents in electronic commerce environments. The existing agents base their search on a predefined list of Web-stores and, as such, they can be qualified as fixed-sample size searching agents. However, with the implementation of new Internet pricing schemes, this search rule evolve toward more flexible search methods allowing for an explicit trade-off between the communication costs and the product price. In this setting, the sequential optimal search rule is a possible alternative. Nevertheless, its adoption depends on its expected performance. The main goal is to analyze the relative performances of two types of search agents on a virtual market with costly information. The following section reviews several existing agents to highlight their flaws and strengths. This review aims to test the theory that agents are a viable alternative to search engines.

2. Overview of intelligent agent

During the last years, the remarkable growth of the Internet caused an increasing demand for more advanced tools capable to assist net-surfers in their search for useful information. In the field of electronic commerce, consumers can already benefit from the use of searching agents that automatically query on-line sellers' catalogues in order to gather information about available products. An example of simple searching agent is BargainFinder who gathers price information about books on behalf of her user. More recent and sophisticated searching agents, as Mpire [www.mpire.com], can screen a wide range of products (computer, software, cosmetics, wine, televisions, etc.) not only by considering their prices, but also by considering their quality attributes. However, the use of electronic agents is still in a nascent phase and, even if we already imagine a near future when consumers and companies will interact by their virtual counterparts (Guttman et al., 1998), it is not clear yet what such an electronic market will look like.

Information agents are agents that have access to at least one, and potentially many information sources. They are able to manipulate information obtained from these sources in order to answer queries posed by users and other information agents (Papazoglou et al., 1992). The information sources may be of many types (example, traditional databases). A number of studies have been made of information agents, including a theoretical study of how agents are able to incorporate information from different sources (Gruber, 1991), (Levy et al., 1994). Another important system in this area is called Carnot (Huhns et al., 1992), which allows pre-existing and heterogeneous database systems to work together to answer queries that are outside the scope of any of the individual databases. (Franklin et al., 1996) define an agent as an autonomous process running on a computer that is able to sense and react to its environment. This agent is able to run without interaction with the user and must therefore be able to make decisions about the environment and the realization of its goals. (Hermans, 1996) and (Jennings et al., 1996) outline several characteristics of software agents. They believe agents require social ability to interact with the user. The agent must be responsive and proactive so it can sense and react to its environment and the users needs. They must be temporally continuous, goal oriented, adaptive and they should be autonomous and able to collaborate with the user and other agents to perform tasks. (Negroponte, 1997) believes that agents are useful not because they can perform tasks a user could not perform on their own using other tools, but because they perform tasks, the user finds trivial or mundane. By delegating the task of information retrieval to the agent, the user is able to direct their attention to tasks that are more enjoyable or make better use of their time. This author suggests that increasing the amount of information that the user has access to on the Internet does not improve the Internet as an information resource. Rather, it makes the process of finding accurate reliable resources that match the user's information need even more difficult. He contends that users do not need more information. They need a relatively small amount of information that is concise, accurate and relevant to them. Therefore, a method of filtering the abundant information, so that only poignant information remains, is required.

Information management in agents is not restricted to the management of user queries. Agents also use a knowledge base to help them manage information, and create a model of the user's information needs. (Maes, 1997) identifies an approach to the design of agents that is "knowledge-based". It involves the agent accruing its knowledge base over time. (Maes, 1997), uses a machine learning approach to the design of agents. We notice that an agent can learn in several ways. Firstly, the agent may monitor user behavior and actions, with the aim of detecting patterns that it can emulate and automate. Secondly, the agent may seek advice from other sources or agents that provide the same service to their user and have more experience.

Negotiation is a critical activity in electronic environments. In general negotiation is defined as an iterative process which aims to achieve a mutually beneficial deal for the seller and buyer (Fisher et al. 1991). Negotiations can be done manually in electronic commerce, for example, by emails, but this is not time and cost-effective. There is a need for automated negotiation. For example, a negotiation process using two intelligent agents to negotiate a solution autonomously would be more efficient and objective. Software agents are currently being used for information retrieval and for offering recommendations such as finding product information, comparing product prices, and offering suggestions on product and services based on customer's interest and preferences (Murugesan, 1998).

Negotiation theory was first used in game theory. Negotiation in game theory is different from real life. The game software does not have to learn to make good decisions. The game has already all needed information for decision making. Still in game theory, we can find two good ideas. Firstly, in game theory, agents have knowledge of other agent negotiation and decision making algorithm. Secondly, game agents have all needed information for negotiating on a certain place and they can use common knowledge instead of its own. Auctioning is most popular and mostly used negotiation strategy. Usually agents are auctioning on goods or services. User creates agent with certain conditions, values, and bidding strategies and agent is bidding in auction instead of the user.

Negotiation Agents can be also used to improve regular person-to-person negotiation. InterNeg project is good example (www.InterNeg.org). These way agents can be used to search, sort, choose, or recommend some information, solution, but final decision is left to the users. Negotiation does not have to end-up with rejecting or accepting. The negotiation result can be data for next negotiation. In this case, agents work as a good secretary.

Automating negotiation for business to business trade has the potential to transform the way in which business is conducted, and improve negotiation trade transactions in terms of speed, efficiency, and quality of contract agreement. There have been recent research advances towards the construction of software capable of automating electronic commerce negotiation. However, there is still much work to be done for this to be achieved. Complicating the automation of trade is the context of ecommerce. Two key features of the electronic commerce trade context are identified by (Zwass, 1996) to be the ability to share and use business information and the evolution and maintenance of business relationships. Business information is the set of data, facts or opinions which directly relates to the conduct of the electronic commerce transaction. An example of this type of information is market information (market price). Another example is the participant information, what ones know about the other participants in the negotiation. Electronic marketplaces such as (Bogdanovych et al., 2004) facilitate ecommerce trade. Within this environmental context, the informational context is rich in diverse, dynamic, and easily accessible business information. A significant problem in automating negotiation in electronic commerce is accounting for the informational context that environments such as (Bogdanovych et al., 2004) provide. The consequence of accounting for the rich sources of information in automating negotiation is that the decisions made reflect those that are appropriate with regards to the environment. The challenge is how to enable automated negotiation software with this property.

With very few exceptions (Kephart et al., 1999), the research available on agent-based markets considered search costs as negligible in the analysis of market evolution. However, we believe that with the evolution of Internet pricing mechanisms and agent intermediation, the search costs will become an important aspect in modeling agent-based markets. Indeed, these two phenomena could change the basic rules of agent interactivity and market structure as we conceive of it today. It is clear that the fast spread of the Internet at global level balanced with bandwidth limited extensibility raises problems related to the Internet providers' quality of service. To avoid Internet congestion, the regulators consider the introduction of new pricing schemes based on the real use of network resources (Mcknight et al., 1997). If such pricing mechanisms will be adopted, the buying agents will cause to their users some "search cost" related to Internet resources usage for communication scopes. Even if this cost is low compared to the price of the product, it is clear that, in the long run, if the aim of the buying agent is to maximize her user's utility, she should consider the incurred search cost in her decisions. Unfortunately the searching rule currently used by the agents does not take these problems into account. Therefore it is important to analyze different other rules that could be used by agents in the future. Indeed, the existing agents base their search on a predefined list of commercial sites and they do not explicitly incorporate the costs associated to the realization of their objective. This kind of search is based on a fixed sample-size searching rule. In this paper, the agents using this rule are named FSS buying agents. However, the economic theory shows that, on a market with costly information, the optimal searching rule is a sequential rule based on a reservation price (Rothschild et al., 1974). The RP buying agents (using an optimal sequential searching rule) would represent a possible alternative to replace the FSS buying agents. Indeed, in presence of search costs, the consumer's objective is not only to minimize the product's purchase price, but also to minimize the communication costs.

In the present study, we compare the FSS buying agents and RP buying agents performances in term of total costs (product price plus total searching cost) paid by the consumers. We try to determinate if it is profitable for the existing searching agents to adopt an optimal sequential searching rule. For this purpose, we analyze a market where FSS buying agents and RP buying agents coexist. In our model, we assume that the search costs correspond to a constant unit cost of communication paid by the agents to have access to the price information of a Website. A lot of research in economics was concerned with game theoretic equilibrium of markets where buyers' search for price information is costly (Diamond, 1971), (Stiglitz, 1989), or where the buyers are in a situation of information asymmetry (Varian, 1980). Closer to our model is the work of (Stahl, 1989). However, while this author considered that fixed-sample-size searchers have complete information of all market prices, we limited their perceptiveness to a reduced set of sellers. In addition, we considered a unit demand and we introduced reservation values for buyers. The main reason for these modifications was that we wanted our model to be closer to the market scenario for electronic agents we have imagined. In this model, we showed that symmetric mixed-strategy equilibrium exists and we compare the performance of the FSS buying agents and RP buying agents. At the theoretical equilibrium, we show that the agents using a sequential searching rule allow consumers to pay lower total costs. On the existing Internet markets, the restrictive assumptions of a game theoretic analysis are very unlikely to be met. In order to relax them, we simulate a market where the sellers use a dynamic pricing strategy, and where the RP buying agents have access only to partial information when they determine their reservation price. The simulations confirm the good performance of the sequential searching rule and show that the agents could adopt it in the future.

Literature indicates that agents are a useful alternative to search engines because the user can delegate the information retrieval task to them. Autonomy, temporal continuity and adaptiveness are some of the aspects of agent functionality that enable an agent to work effectively on behalf of a user.

The chapter proceeds as follows. The market model for electronic agents that we propose and the game-theoretic equilibrium are presented in Sections 2 and 3. In Section 4, we compare the performances of the two types of searching agents on the market. In Section 5, we present and analyze the results of our simulations concerning the performance of the two searching rules in various configurations of the market. We present our conclusion in Section 6 together with some closing remarks on future developments.

3. Theoretical analysis of the agent-based market equilibrium

In this section, we describe an Internet agent-based market where agents representing companies or consumers transact a homogenous product (good or service). On the market, agents act on their users' behalf by trying either to maximize profits or to find "good deals".[1] In what follows, we will refer to agents owned by companies as "*selling agents*" and to agents owned by consumers as "*buying agents*". On the analyzed market, we assume that the number M of buying agents is significantly higher than the number N of selling agents ($M >> N$). The number of agents on the market is considered fix over time. As the commercialized product is homogenous, the N selling agents compete with each other on the market in terms of price. We suppose that each selling agent has the same constant unit production cost v and the same fix production cost FC. For convenience, these two production costs are considered to be nil.[2] Given that the reproduction costs are nil, each selling agent is able to satisfy at any time all the buying demands she receives. In our model, we completely ignore the possibility of price negotiation between buying agents and selling agents. The only permitted "bargaining" consists in selling agents making a take-it or leave-it offer to any buying agent who visits them.

On the considered market, all buying agents incur in their search process a positive cost c for each selling agent they visit but they differ by their search strategy. Thus, two types of buying agents coexist on the market: fixed-sample-size buying agents (FSS buying agents) and reservation-price buying agents (RP buying agents).[3] Each buying agent, whatever her type, has a unit demand constraint by a reservation value r. This reservation value is assumed to be equal among the buying population and should be interpreted, as the maximum-posted price of the selling agent a buying agent is willing to accept. The FSS buying agents correspond to the existing searching agents and use a predefined list of n transaction partners. These agents are in proportion w_1 on the market. A FSS buying agent will buy at the lowest price she was proposed, if lower than her reservation value r. We assume here that the sample-size n is exogenously given and is identical for all FSS buying agents. However, even if the list of selling agents is predefined, that list varies from one buying agent to another, which allows a posteriori for different buying agents to find

[1] Even if real users are an essential component for the existence of an agent-based market, the present study exclusively focuses on the strategic interaction between agents. Indeed, we assume that the agents are endowed with all relevant information they need to define their goals.

[2] Our analysis still holds for any positive value of these two parameters. Moreover, one can note that the assumption of zero production costs seems rather adequate on the Internet especially for products such as information goods (digital books, videos, etc.). Indeed, for these products the reproduction costs are nil (Varian, 2000).

[3] In economic theory, this two search rules are often qualified as "non-optimal" for the fixed-sample-size search rule and "optimal" for the reservation-price search rule (Rothschild, 1974).

different prices for the product. The remaining buying agents (proportion $w_2 = 1 - w_1$) are RP buying agents and proceed to a sequential search for transaction partners. If we consider *F(p)* to be the cumulative price dispersion on the market, the reservation-price rule used by the RP buying agent can be formalized as follows. When facing a current posted price *q*, the RP buying agent expected gain for searching once more is given by:

$$g(q) = \int_0^q (q - p)dF(p) = \int_0^q F(p)dp \tag{2}$$

where *q* is the current price and *p* is the posted price of the next visited selling agent. From an economic point of view, it is optimal to keep searching while the expected gain of an additional search exceeds the search cost (Rothschild, 1974). As a result, the reservation price *R* must satisfy: *g(R) = c*.

4. Market equilibrium

In order to compute the game theoretic equilibrium of the market model described in the previous section, we proceed to a strategic analysis of selling agents behavior on the market. With the previous market description, selling agents play a Nash non-cooperative game among themselves and a Stackelberg game against buying agents who take the prices they find as given. Because there is no pure-strategy equilibrium in our model (Varian, 1980), (Stahl, 1989), we analyzed symmetric mixed-strategy equilibrium with each selling agent randomly choosing a price with respect to the same equilibrium price distribution. We note by *f(p)* the equilibrium price distribution, and by *F(p)* the associated cumulative price distribution. Facing the same market price distribution and being characterized by the same set of parameters (search cost and reservation value), there is no reason for identical RP buying agents to solve their search problem in different manners. As a result, in equilibrium, all the RP buying agents choose the same reservation price *R*.
With this remark we can proceed to the computation of the market equilibrium. First, some preliminary characteristics of the Nash-Equilibrium probability distribution are established. Second, the optimal behavior of selling agents and the market equilibrium are computed. During these two steps the reservation price *R* is assumed exogenous which confers a conditional aspect to the analyzed market equilibrium. This aspect is emphasized by using the notation *F(p, R)* for the Nash-Equilibrium cumulative price distribution conditional on *R*. Finally, the existence of an endogenous reservation price *R* is established and an analytical expression for this price is computed.

4.1 Some preliminary results

Before computing the symmetric Nash equilibrium in mixed-strategy conditional on *R*, two properties of such a distribution need to be established, more precisely that it is atomless (Lemma 1.) and that it has an upper bound (Lemma 2.). Only intuitive proofs of these results will be given here. For more formalized explanations, see Stahl [11] and Varian [13].
Lemma 1. If *f*(*p*, *R*) is a Nash-Equilibrium distribution conditional on reservation price *R*, there can be no mass point[4] in this distribution, except at the lowest price.

[4] Recall that *p* is a mass point of a probability density function if there is positive probability concentrated at *p*.

Proof. Let's assume the probability distribution has a mass point at p^* (p^* other than the lowest price). Then, for any perceptiveness $n \geq 2$ of FSS buying agents, there is some positive probability that a buying agent visiting n selling agents only finds out about selling agents charging price p^*. In this particular scenario, if one of these selling agents lowers her price by an epsilon, she gains all the FSS buying agents as certain customers, thus increasing her profits. As a result, we can conclude that there cannot be a two-price equilibrium or any equilibrium price distribution with a mass point other than at the lowest price.

Lemma 2. If $F(p, R)$ is a Nash-Equilibrium distribution conditional on reservation price R, the maximal element of its support, denoted $p_{\max}$, is the minimum value between R and r: $p_{\max} = \min\{R, r\}$.

Proof. To prove this result two aspects need to be established: $p_{\max}$ can neither be higher, nor lower than $\min\{R, r\}$. Let's first consider that $p_{\max} < \min\{R, r\}$. Provided that the equilibrium distribution is atomless, when fixing a price $p_{\max}$, selling agents only win profits from RP buying agents. However, by slightly increasing their prices they lose no customers and they increase their profits. This situation can't be equilibrium. Let's now consider the opposite case where $p_{\max} > \min\{R, r\}$. If $r < R$ the proof is obvious as selling agents can only expect no sales by fixing a higher price than r, as no buying agent will pay more than her reservation value r for the product. If $r > R$, fixing the price $p_{\max}$ causes selling agents to lose all their customers: RP buying agents won't buy as the price is higher than their reservation price R, while for FSS buying agents the probability to find a lower price is one ($F(p, R)$ is atomless). So, the expected profits of the selling agent are nil. By lowering the maximal price to R, selling agents can expect to attract at least $1 / N$ RP buying agents, which gives them positive profits. With these remarks, one can conclude that $p_{\max} = \min\{R, r\}$.

4.2 Computation of the conditional mixed strategy equilibrium

The two properties of the probability distribution established earlier enable us to compute the equilibrium probability distribution conditional on R. As we showed that all the prices practiced on the market are lower than R (cf. Lemma 2.), in equilibrium, all the RP buying agents buy from the first store they visit. It follows that only FSS buying agents engage in active search activities. The condition for $f(p)$ to be an equilibrium probability distribution for the selling agent i ($i = 1, ..., N$) is that it should maximize her expected profits. In other terms, given that the other N-1 selling agents use mixed-strategies by randomly choosing a price according to $f(p)$, the selling agent i's profits by choosing any price from the support of $f(p)$ should be the same. Otherwise, she would be better off by choosing the price with the highest expected profits. For this to be true, for some positive value K, we need two conditions to be satisfied: (i). $\pi_i(p_i) \leq K$ for every possible price p and (ii). $\pi_i(p_i) = K$ for all the prices p effectively played in equilibrium.

By fixing a price of p_i while all other sellers use a mixed-strategy $f(p)$, the selling agent i's expected profits depend on the demand she will face: $\pi_i(p_i) = p_i D_i(p_i, p_{-i})$ where p_{-i} is the vector of prices chosen by all the sellers and $D_i(p_i, p_{-i}) = D_{i, w_1}(p_i, p_{-i}) + D_i$ where $D_{i, w_1}(p_i, p_{-i})$ is the expected demand from FSS buying agents and $D_{i, w_2}(p_i, p_{-i})$ is the expected demand from RP buying agents. As FSS buying agents have a n-perceptiveness, for such an agent to buy from selling agent i, two conditions need to be satisfied. First, selling agent i should be in the n-size sample, which happens with probability n / N. Second, p_i needs to be the lowest price between the n prices sampled, which happens with [5] probability $[1 - F(p_i)]^{n-1}$. As a result $D_{i,w_1}(p_i, p_{-i}) = w_1 M(n / N)[1 - F(p_i)]^{n-1}$. As p_i is always lower than R and so are the other selling agents' prices on the market, selling agent i can expect that a $1 / N$ share of RP buying agents will buy from its store independently of the offered price.[6] The corresponding demand is: $D_{i,w_2}(p_i, p_{-i}) = w_2 M(1 / N)$. It follows that:

$$\pi_i(p_i) = p_i\left[w_1 M\frac{n}{N}[1 - F(p_i, R)]^{n-1} + w_2 M\frac{1}{N}\right] \tag{3.1}$$

In order for $F(p_i, R)$ to be a Nash-Equilibrium distribution, the selling agent i must expect equal profits by choosing any price with a non-negative support. In other words, we need the following condition to be true for all the prices p_i effectively played in equilibrium: $\pi_i(p_i) = \pi$. As for $p_i = p_{\max}$ we have $F(p_{\max}) = 1$, we can compute the value of π:

$$\pi = \frac{p_{\max} w_2 M}{N} \tag{3.2}$$

Solving $\pi_i(p_i) = \pi$, we obtain:

$$F(p_i, R) = 1 - \left[\frac{w_2}{n w_1}\left(\frac{p_{\max}}{p_i} - 1\right)\right]^{\frac{1}{n-1}} \tag{3.3}$$

The density function $f(p_i, R)$ is the derivative of $F(p_i, R)$ with respect to p_i:

$$f(p_i, R) = \frac{w_2}{n(n-1)w_1}\left[\frac{w_2}{n w_1}\left(\frac{p_{\max}}{p} - 1\right)\right]^{-\frac{n-2}{n-1}} \frac{p_{\max}}{p^2} \tag{3.4}$$

In order for $F(p_i, R)$ to be a true probability distribution, it should only take positive values. So, we can compute the lowest bound of the support of f, $p_{\min}$, whose value is such that $F(p_{\min}, R) = 0$, which yields:

$$p_{\min}(R) = \frac{p_{\max} w_2}{n w_1 + w_2} \tag{3.5}$$

At this stage we have a complete characterization of the Nash Equilibrium distribution conditional on R.

4.3 Existence of an endogenous R

Until now, we have supposed R exogenously given. For our problem to be completely solved, we have to verify that there exists an endogenous reservation price R consistent with

---

[5] Given that there are no mass points in the probability distribution, we can ignore the possibility of a tie at a price of p_i.

[6] Given that at equilibrium all the prices will be lower than R, RP buying agents are equally likely to buy from any seller.

the previously determined distribution $F(p, R)$. As stated earlier, RP buying agents choose their reservation price to be the solution R^* of the following equation, provided that $R^* \leq r$:

$$g(R) = \int_{p_{min}(R)}^{R} F(p,R)dp = c \tag{3.6}$$

Note that RP buying agents will never choose a reservation price higher than their reservation value r. The condition (3.6) can be rewritten as:

$$\begin{aligned} &H\left(p,R^*,c\right) = 0 \quad \text{where} \\ &H(p,R,c) = \int_{p_{min}(R)}^{R} F(p,R)dp - c \end{aligned} \tag{3.7}$$

In order to facilitate the analysis, we first concentrate on the case where we have a solution $R^* \leq r$. It follows that $p_{max} = R^*$. Using the equations (3.3) and (3.5), the equation (3.7) becomes:

$$H(p,R^*,c) = \int_{\frac{w_2R^*}{nw_1+w_2}}^{R^*} \left[1 - \left[\frac{w_2}{nw_1}\left(\frac{R^*}{p} - 1\right)\right]^{\frac{1}{n-1}}\right]dp - c \tag{3.8}$$

After computations, we obtain an analytical expression for R^*:

$$R^* = \frac{c}{1 - \alpha - \beta I_n} \tag{3.9}$$

where $\alpha = \dfrac{w_2}{nw_1 + w_2}$, $\beta = \left(\dfrac{w_2}{nw_1}\right)^{\frac{1}{n-1}}$ and $I_n = \displaystyle\int_0^{(1/\alpha)-1} \frac{t^{1/(n-1)}}{(t+1)^2} dt$

As the uniqueness of such a solution is obvious, a necessary condition for this R^* to be a consistent reservation price is that it should be positive:

$$1 - a - bI_n > 0 \tag{3.10}$$

Let's now consider what happens if the solution R^* is higher than r. In this case, the RP buying agents will always fix their reservation price at r and p_{max} will equal r. Therefore, under the condition (3.10), we can formally define a consistent reservation price R for RP buying agents: $R = \min\{R^*, r\}$. So, the complete description of the market equilibrium for selling agents behavior is given by the equations (3.3).

5. Compared expected performances of the two types of buying agents

In this section we compare the performance of RP buying agents versus FSS buying agents in term of total costs paid by the consumers. The consumer's total cost is obtained by summing the price paid for the product and the total searching cost incurred by the agent.

The expected total cost for a consumer who uses an FSS buying agent is given by the following expression:

$$CT_{FSS}(n) = cn + \overline{p}_n \tag{4.1}$$

where $CT_{FSS}(n)$ represents the expected total cost for a searching agent having a sample size n, $\overline{p}_n$ represents the expected price paid by the consumer and cn is the total search cost paid for using this agent. On the considered market, the expected price $\overline{p}_n$ paid by an FSS buying agent with a sample size N is given by:

$$\overline{p}_n = \int_{p_{min}}^{p_{max}} [1 - F(p)]^{n-1} nf(p)pdp \tag{4.2}$$

The expected total cost for this agent is:

$$CT_{FSS}(n) = cn + \int_{p_{min}}^{p_{max}} [1 - F(p)]^{n-1} nf(p)pdp \tag{4.3}$$

In order to determine the expected total cost of using an RP buying agent, we previously showed that at equilibrium such agents buy in the first store that they visit. Thus, an RP buying agent will pay only one search cost c. The expected total cost is then given by the following expression:

$$CT_{RP} = c + \int_{p_{min}}^{p_{max}} pf(p)dp \tag{4.4}$$

In order to compare the performance of these two types of searching agents, we must analyze the sign of the difference between their total costs:

$$\Delta CT(n) = CT_{FSS}(n) - CT_{RP} = c(n-1) + \int_{p_{min}}^{R} (1 - F(p))[(1 - F(p))^{n-1} - 1]dp \tag{4.5}$$

Replacing $F(p)$ by its analytical expression (cf. equation (3.3)), we can show that $\Delta CT(n)$ is positive for every sample size of FSS buying agents, every proportion of the two agent types on the market (w_1 and w_2) or every search cost value c. We can conclude that, at equilibrium, the RP buying agent always allow the consumers to pay lower total costs than those paid by with an FSS buying agent. The theoretical model shows that it is profitable for the searching agents to evolve toward the use of a sequential searching rule with reservation price in order to satisfy at best consumers needs. This result is coherent with the economic literature, which considers the RP rule to be optimal for searching on a market with costly information.

6. Proposed framework

The results obtained in the previous section concerning the superiority of the RP buying agents over the FSS buying agents' are strongly dependent on the assumptions made.

Indeed, as the RP buying agents are perfectly informed about the market structure and there is common knowledge of rationality, they are able to determine seller's mixed-strategy equilibrium and fix their reservation price according to this distribution. These assumptions are particularly restrictive on real market. Indeed, in practice it is unlikely for the RP buying agents to have a perfect knowledge about the market structure and sellers price their products according to the equilibrium's distribution probability previously established (in order to compute the equilibrium price distribution the sellers also need to be perfectly informed about the market structure). A more realistic analysis seems necessary, especially as some theoretical studies (Gastwirth, 1976) show that small anticipation error can considerably deteriorate the RP buying agents performance. Before concluding about the superiority of the RP buying agents' searching strategy over FSS buying agents in the context of a real market, it's important to study the impact of the introduction of partial information. Indeed, partial information about the market could increase considerably the RP buying agents total search cost whereas the fixed sample-size searching rule limits the FSS buying agents' search cost. According to other studies that try to relax the assumptions of the economic models (Kephart et al., 1999) in analyzing Internet markets, we simulate a market where the selling agents try to maximize their profit by using a dynamic pricing strategy requiring only partial information, and where RP buying agents determine their reservation price based on a partial degree of information on market's price distribution.

6.1 Sellers' pricing strategy and the RP buying agents' information

In our simulations, we consider that the selling agents use a dynamic pricing strategy based on the gradient heuristic. Sellers' incentive to adopt such pricing strategy on the Internet has already been presented in other research (Kephart et al., 1999). Indeed, this dynamic pricing strategy does not require information about the market structure and it allows the sellers to enjoy high profits by facilitating tacit collusions. During a given period, a selling agent using the gradient heuristic decide to reduce or to increase her price according to the observed variations of her profits following her last price modification. For example, if the preceding decision of the selling agent was to increase her price and she observed an increase in her profits, then she will reproduce the same action (price increase). In the opposite case, if the price modification lee to a reduction in her profits, she will do an opposite action, a price reduction. To define more precisely this selling agents' pricing strategy, it is necessary to fix two parameters: the amount Δ of the possible price variations and the announced price in the first period. In our simulations, the announced price, at the beginning, by a selling agent is chosen randomly in the interval $[0, r]$. With each price modification, the increment or the decrement Δ is selected randomly between values 1, 2, 3, 4 or 5 if the selling agent decides to increase her price or -1, -2, -3, -4 or -5 if the selling agent decides to decrease her price. We can note that this pricing strategy is easy to implement by a seller as it does not require any preliminary information neither on the competitors' behavior, nor on the demand.

As we have already mentioned, on traditional markets it is difficult for the RP buying agents to use the real price distribution in order to determine their reservation price. Within the framework of our simulations, we assume that the RP buying agents can calculate their reservation price by using a partial degree of information γ on the prices in a period. This information degree is assumed to be identical for all the RP buying agents evolving on the market, and can be interpreted as the number of prices an agent used to calculate her reservation price. For example, if $\gamma = 0{,}1$, the searching agents use 10% of the sellers' prices so us determine her reservation price.

6.2 Simulations

In our simulations, we fix the number of buying agents to M = 1000 and the numbers of selling agents to N = 20. We consider that the two types of searching agents are in equal proportion on the market w_1 = 0,5 and w_2 = 0,5 (i.e., 50% FSS buying agents and 50% RP buying agents). The buying agents' reservation value is equal to r = 50 and the communication cost is equal to c = 2. As we only want to study the performances of the two types of agents, the only parameters that we vary from one simulation to another are the RP buying agents' information degree γ and the FSS buying agents' sample size n. In our simulations, these two parameters can take the values γ = {0,1; 0,3; 0,5} and n = {2; 4; 6}. We simulate the market evolution on T = 30 000 periods and we consider that the selling agents can readjust their price rate at λ = 0,1 per period.

<table>
<tr><th colspan="3" rowspan="2"></th><th colspan="3">Information RP (γ)</th></tr>
<tr><th>0,1</th><th>0,3</th><th>0,5</th></tr>
<tr><td rowspan="6">FSS simple-size (n)</td><td rowspan="2">2</td><td>FSS average price</td><td>16,54</td><td>19,10</td><td>27,60</td></tr>
<tr><td>RP average price</td><td>11,05</td><td>8,93</td><td>11,50</td></tr>
<tr><td rowspan="2">4</td><td>FSS average price</td><td>9,54</td><td>11,64</td><td>16,61</td></tr>
<tr><td>RP average price</td><td>10,71</td><td>9,71</td><td>11,53</td></tr>
<tr><td rowspan="2">6</td><td>FSS average price</td><td>5,84</td><td>7,99</td><td>11,97</td></tr>
<tr><td>RP average price</td><td>9,49</td><td>9,39</td><td>11,47</td></tr>
</table>

Table 1. Average prices paid by the FSS and RP buying agents

<table>
<tr><th colspan="3" rowspan="2"></th><th colspan="3">Information RP (γ)</th></tr>
<tr><th>0,1</th><th>0,3</th><th>0,5</th></tr>
<tr><td rowspan="6">FSS simple-size (n)</td><td rowspan="2">2</td><td>FSS search</td><td>2</td><td>2</td><td>2</td></tr>
<tr><td>RP search</td><td>3,42</td><td>3,68</td><td>4,49</td></tr>
<tr><td rowspan="2">4</td><td>FSS search</td><td>4</td><td>4</td><td>4</td></tr>
<tr><td>RP search</td><td>3,42</td><td>3,72</td><td>4,24</td></tr>
<tr><td rowspan="2">6</td><td>FSS search</td><td>6</td><td>6</td><td>6</td></tr>
<tr><td>RP search</td><td>3,02</td><td>3,71</td><td>4,25</td></tr>
</table>

Table 2. Average search numbers for the FSS and RP buying agents

The results of our simulations in term of average paid prices, average number of searches carried out and average total costs for the two types of agent are presented in the tables below. We can notice that for the RP search agents the average number of searches is simply obtained by dividing the difference between the average price paid and the average total cost by the communication cost.

			Information RP (γ)		
			0,1	0,3	0,5
FSS simple-size (n)	2	Total cost FSS	20,54	23,10	31,60
		Total cost RP	17,89	16,30	20,49
	4	Total cost FSS	17,54	19,64	24,61
		Total cost RP	17,55	17,15	20,06
	6	Total cost FSS	17,84	19,99	23,97
		Total cost RP	15,90	16,82	19,93

Table 3. Average total costs for the FSS and RP buying agents

In term of average total costs, simulations show that RP buying agents' performance is quite good compared to FSS buying agents' performance. Moreover, this result still holds even if these agents have access to little information on market prices. However, we can notice that more RP agents have a significant degree of information on market prices, more their compared performance to FSS agents' is important. A somewhat counter intuitive result is that on increase in the RP buying agents' information degree leads to price raise on the market. This result is explained by the adaptability of the seller's strategy to the market configuration. Indeed, when the RP buying agents' information increases, the sellers are encouraged to specialize either on high prices, or on low prices, which leads to an increase in the prices dispersion on the market. In this case, FSS buying agents have a high probability to have high prices in their sample n, whereas RP buying agents search more. Nevertheless, when the FSS buying agents' sample size increases the latter finds lower prices. Our simulations confirm that RP buying agents can represent a good alternative for searching commercial information on the network.

7. Conclusion

In this study, we analyzed the possible evolution of the fixed sample-size searching rule used by the existing agents towards an optimal sequential searching rule with reservation price. Indeed, as it was underlined, a costly information search requires the agents to make a trade-off between communication costs and product prices. In order to study this possible evolution, we proposed a market model where FSS and RP buying agents coexist. A theoretical analysis of the market equilibrium showed that RP buying agents always allowed the consumers to pay lower total costs than FSS buying agents. Moreover, this result holds when some assumptions of the game theory model are relaxed by simulating the dynamics of a market where the selling agents use a dynamic pricing strategy and where the RP buying agents can fix their reservation price only an the basis of partial information about the prices charged on the market. We can thus conclude that in the future the sequential searching rule could be a good alternative for searching agents.

This study has reviewed the main concepts and issues associated with the theory and practice of intelligent agents. It has drawn together a very wide range of material, and has hopefully provided an insight into what an agent is, how the notion of an agent can be formalized, how appropriate costly information search agent can be designed and implemented. The subject matter of this review is important because it is increasingly felt, both within academia and industry, that intelligent agents will be a key technology as computing systems become ever more distributed, interconnected, and open. In such environments, the ability of agents to autonomously plan and pursue their actions and goals, to cooperate, coordinate, and negotiate with others, and to respond flexibly and intelligently to dynamic and unpredictable situations will lead to significant improvements in the quality and sophistication of the software systems that can be conceived and implemented, and the application areas and problems which can be addressed.

Several extensions of our study are possible. First of all, it would be necessary to relax the assumption that the product sold on the market is an homogeneous good. Indeed, on the Internet, one of the most important dimensions of competition between the sellers is the quality of their products (Bakos et al., 1997), (Delong, 1998). Moreover, the Internet offers new differentiation opportunity for sellers, like personalization or bundling. Another extension is the introduction of a more complex transaction mechanism to model the negotiation between sellers and the searching agents. Negotiation is an important aspect in distribution of rare resources on the network. A third extension would be the introduction of an intermediary that will charge a fee to give agents access to his data-bases containing more relevant information about the market. The presence of this type of intermediation could evolve in the future (Bailey, 1997) and has the potential to influence agents' searching rule.

8. References

Bakos J.Y. (1997). Reducing Buyer Search Costs: *Implications For Electronic Marketplaces. Management Science*, Vol. 43, No. 12, pp. 1676-1692

Bailey J., Bakos, J.Y. (1997). An Exploratory Study Of The Emerging Role Of Electronic Intermediaries, *International Journal Of Electronic Commerce*, Vol. 1, No. 3, pp. 7-21

Bogdanovych A., Berger H., Simoff S., Sierra C. (2004). Ecommerce environments as 3d electronic institutions, *In Proceedings of the IADIS International e-Commerce Conference*, pp. 237–242, Lisbon, Portugal.

Campbell M., Gozinski A. (2001). An Information Agent Model, *Technical Report*, TR C01/19, Deakin University. Melbourne.

Cournot A.G. (1838). Recherches Sur Les Principes Mathematiques De La Theorie De La Richesse, *Hachette*, Paris

Delong J.B., Froomkin, A.M. (1998). The Next Economy?. In Hurley D., Kahin B. & H. Varian (Eds.), *Internet Publishing And Beyond: The Economics Of Digital Information And Intellectual Property*, Mit Press, Cambridge

Diamond P.A. (1971). A Model Of Price Adjustment, *Journal Of Economic Theory*, Vol. 3, No. 2-4, pp. 156-168

Fisher R., Ury W., Patton B. (1991). Getting to Yes: Negotiating Agreement Without Giving *In, 2nd ed. Boston, Houghton Mifflin*

Franklin S., Graesser A. (1996). Is it an Agent, or just a Program?: A Taxonomy for Autonomous Agents, *Third International Workshop on Agent Theories*, Architectures, and Languages, Springer-Verlag.

Gastwirth J.L. (1976). On Probabilistic Consumer Search For Information. *Quarterly Journal Of Economics*, Vol. 90, No. 1, pp. 38-50

Gruber T. R. (1991). The role of common ontology in achieving sharable, reusable knowledge bases. In Fikes, R. and Sandewall, E., editors, *Proceedings of Knowledge Representation and Reasoning (KR&R-91)*. Morgan Kaufmann Publishers: San Mateo, CA

Guttman R., Moukas A., Maes P. (1998). Agent-Mediated Electronic Commerce: A Survey, *Knowledge Engineering Review*, Vol. 13, No. 2, pp. 147-159

Hermans B. (1996). Intelligent software agents on the internet: An inventory of currently offered functionality in the information society and a prediction of (near-) future developments, *Ph.D. Thesis*, Tilburg University. Tilburg.

Huhns M. N., Jacobs N., Ksiezyk T., Shen W. M., Singh M. P., and Cannata P. E. (1992). Integrating enterprise information models in Carnot. In *Proceedings of the International Conference on Intelligent and Cooperative Information Systems*, pages 32-42, Rotterdam, The Netherlands.

Jennings N., Wooldridge M. (1996). Software Agents, *IEE Review*, January, pp. 17-20.

Kephart J., Greenwald A. (1999). Shopbot And Pricebots, *Proceedings Of The International Joint Conferences On Artificial Intelligence*, Stockholm, Sweden

Levy A. Y., Sagiv Y., Srivastava D. (1994). Towards efficient information gathering agents. In Etzioni, O., editor, *Software Agents - Papers from the 1994 Spring Symposium (Technical Report SS-94-03)*, pages 64-70. AAAI Press.

Lieberman H. (1997). Autonomous Interface Agents, Henry Lieberman, Internet, *lieber.www.media.mit.edu/*

Maes P. (1997). Agents that Reduce Work and Information Overload, *Software Agents,* J. Bradshaw. AAAI, Menlo Park.

Mcknight L.W., Bailey J.P. (1997). Internet Economics, *The Mit Press*, Cambridge

Murugesan S., (1998). Intelligent Agents on the Internet and Web, *Proceedings of the IEEE Region IO Conference*, Tencon'98, New Delhi

Negroponte N. (1997). Agents: From Direct Manipulation to Delegation, *Software Agents.* J. Bradshaw. AAAI and MIT Press, Menlo Park.

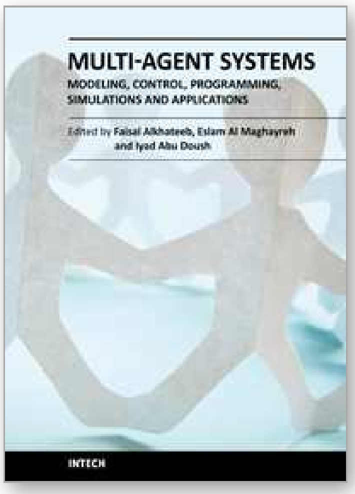
Papazoglou M. P., Laufman S. C., Sellis T. K. (1992). An organizational framework for cooperating intelligent information systems. *Journal of Intelligent and Cooperative Information Systems*, 1(1):169-202.

Rothschild M. (1974). Searching For The Lowest Price When The Distribution Of Prices Is Unknown, *The Journal Of Political Economy*, Vol. 82, No. 4, pp. 689-711

Stahl D.O. (1989). Oligopolistic Pricing With Sequential Consumer Search, *American Economic Review*, Vol. 79, No. 4, pp. 700-712

Stiglitz J.E. (1989). Imperfect Information In The Product Market, *In Handbook Of Industrial Organization*, Schmalensee R. & R.D. Willig, North Holland, New-York, pp. 769-847

Varian H. (1980). A Model Of Sales, *American Economic Review*, Vol. 70, No. 4, pp. 651-659
Varian H. (2000). Buying, Sharing And Renting Information Goods, *Working Paper Series*, University of California at Berkeley.
Voorhees E. M. (1994). Software agents for information retrieval. In Etzioni, O., editor, *Software Agents - Papers from the 1994 Spring Symposium (Technical Report SS-94-03)*, pages 126-129. AAAI Press.
Zwass V. (1996). Electronic commerce: Structures and issues, *Journal of Electronic Commerce*, vol. 1(1), pp. 3–23



Multi-Agent Systems - Modeling, Control, Programming, Simulations and Applications
Edited by Dr. Faisal Alkhateeb

ISBN 978-953-307-174-9
Hard cover, 522 pages
Publisher InTech
Published online 01, April, 2011
Published in print edition April, 2011

A multi-agent system (MAS) is a system composed of multiple interacting intelligent agents. Multi-agent systems can be used to solve problems which are difficult or impossible for an individual agent or monolithic system to solve. Agent systems are open and extensible systems that allow for the deployment of autonomous and proactive software components. Multi-agent systems have been brought up and used in several application domains.

How to reference
In order to correctly reference this scholarly work, feel free to copy and paste the following:

Dorin Militaru (2011). Negotiation in Multi-Agent Environments, Multi-Agent Systems - Modeling, Control, Programming, Simulations and Applications, Dr. Faisal Alkhateeb (Ed.), ISBN: 978-953-307-174-9, InTech, Available from: http://www.intechopen.com/books/multi-agent-systems-modeling-control-programming-simulations-and-applications/negotiation-in-multi-agent-environments

InTech Europe
University Campus STeP Ri
Slavka Krautzeka 83/A
51000 Rijeka, Croatia
Phone: +385 (51) 770 447
Fax: +385 (51) 686 166
www.intechopen.com

InTech China
Unit 405, Office Block, Hotel Equatorial Shanghai
No.65, Yan An Road (West), Shanghai, 200040, China
中国上海市延安西路65号上海国际贵都大饭店办公楼405单元
Phone: +86-21-62489820
Fax: +86-21-62489821

© 2011 The Author(s). Licensee IntechOpen. This chapter is distributed under the terms of the Creative Commons Attribution-NonCommercial-ShareAlike-3.0 License, which permits use, distribution and reproduction for non-commercial purposes, provided the original is properly cited and derivative works building on this content are distributed under the same license.