A formal approach to test commercial strategies: Comparative study using Multiagent-based techniques

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***Abstract*— This paper presents a multiagent recommendation system (RecMAS) able to coordinate the interactions between a user agent (AgUser) and a set of commercial agents (AgComs). It provides a useful service for monitoring changes in the AgUser's beliefs and decisions based on two parameters: (i) the strength of its own beliefs and (ii) the strength of the AgComs' suggestions. The system was used to test several commercial activities in a shopping centre where the AgComs provided information to an AgUser operating in a wireless device (PDA, mobile phone, etc.) used by the client. The AgUser received messages adapted to the preferences of the client. Using a theoretical model and a set of simulation experiments, several commercial strategies were obtained. This paper concludes with a presentation of a prototype in a real shopping centre.**

***Index Terms*— SocioConfiguration, Multiagent systems, Agent-based social simulation.**

I. Introduction

Models of artificial societies from different perspectives are useful in a large number of applications. Currently, there exist several different mathematical models that try to explain what types of relations are established in complex social systems [1]. Traditionally, theoretical models used to analyze complex social systems come from the field of social sciences, using qualitative techniques [2] but at present, new models from a quantitative perspective have started to be proposed [3]; in particular, models based in the theories of complexity [4] and emergent phenomena [5]. Nevertheless, although these models include very complex characteristics related with different domains, generally they do not take into consideration complex internal states. In this paper, Agent-based modelling is used to test formal models and techniques of the area of the multiagent systems are used for the design and implementation stage. Agent-based systems and multiagent systems [6,11] gather very interesting techniques in order to develop tools which can help us to describe (quantitatively) processes of change of beliefs and social adaptation.

The paper is divided in the following parts: section 2 provides a mathematical approach of the system describing the type of interactions between the agents in the proposed model. Briefly, there are *N* BDI-agents, one of which, the AgUser, is able to buy products in a virtual shopping centre stores adapted to a set of preferences. The *N–1* remaining agents, AgCom, propose changes in the beliefs of the AgUser involving purchase of new products.

In the section 3 is described how beliefs change due to social interaction and the relation between the importance of a belief and the social impact. It is shown how the AgUser's immediate beliefs depend on the position in the shopping area (i.e., based on the social interactions). Results are obtained by testing different strategies in a platform of agents based modelling (NetLogo).

In section 4 it is analyzed and showed the process of implementation. It is reproduced the set of behaviours found in the previous section by using Agent-oriented software engineering techniques. In particular, GAIA methodology for designing and analyzing stages, and 3-APL for the implementation on mobile devices of social phenomena that emerge in the system and different results obtained from the simulation of the system's behaviour.

The last two sections are faced to practical issues: section 5 is focused in aspects of optimizing and section 6 describes the results of a real trial in a shopping centre.

II. Multiagent Recommendation Model

There are a huge amount of references on general simulation models. However, the problem and proposed model is focused on the simulation of shopper behavior in physical spaces [22,23,24,25]. In this more specific context, it will be proposed our own framework along this section.

Let's consider a 2-dimensional virtual shopping centre of area *A* where a community of *N* agents exists. N – 1 agents are AgComs which recommend the acquisition of products, and an AgUser which has "money" to buy them. In order to have a spatial description of the agents' system, it is assumed that the centre is divided in z sub-areas $A^* = A/z$ with N_j agents, *i.e.,* the number of agents in the sector *j*.

The number of the AgUser's beliefs, *m,* is shown below and the AgUser's belief concerning a problem is represented by the parameter α_i.

$$A = \{\alpha_i\}_{i=1,\dots,m} \qquad \alpha_i \in \{-r,\dots,-1,0,1,\dots,r\} \qquad (1)$$

The parameter α_i can change from the interaction with other agents or new external information. It is assumed that negative values represent a pre*disposition to reject a proposed task*. Positive values represent a *predisposition for action*, and values in the intermediate region of the interval, a *neutral position waiting for new information*.

A. Dynamic of the belief change in agents

This section starts with the equations for the dynamic of: (i) AgUser 's movements through the shopping centre and (ii) changes in preferences as a consequence of the interaction with several AgComs. It is suposed that: the AgUser starts the visit to the virtual shopping centre (area *A)* in a sub-area referred as k_0 (see figure 1a); it engages in purchases in sector *ks* with the distance between both positions (which coincides with the diagonal of the virtual environment) referred to as *D*(*A*); the AgUser can go to any of the places around him (8 places in the best case, see figure 1b); and, following the shortest route from *k* ,where it starts, to the final state *ks*. The route ϕ(***k0***, ***ks***) is represented in figure (1a) which joins the "entrance sector" and the shopping sub-area. We refer as φ(*k*, ***ks***) the route that the AgUser would follow from another point *k* to ***ks***. Supposing that AgUser is stated in the position ***ki*** and has got belief ***αi*** then the equation of the AgUser's movement -denoted as *σ*(***ki***, ***kj***)-, from its actual position ***ki*** to one of the closer positions is as follows:

$$k_j \in V_{ki} \;\; ^\wedge \;\; k_i \rightarrow V_{ki} = \{\, k_i^1, k_i^2, k_i^3, \ldots., k_i^8\} \qquad (2)$$

So,

- If the number of AgComs in ***ki*** with belief ***αi*** *(which coincides* with the AgUser's belief) is larger than the number of AgComs that share another belief ***αj*** with $j \neq i$, then the belief ***αi*** is reinforced and the AgUser chooses the path to sector ***ks,*** represented by,

$$\varphi(K, K_s) = K_s - K \qquad (3)$$

- If the number of AgComs in ***ki*** with a different belief ***αj*** from ***αi*** is larger than that of those that share ***αi***, the AgUser moves randomly to one of the nearest sectors $k_j \in V_{ki}$ in order to attain more beliefs. The formula that summarizes both of the AgUser's circulation strategies is shown below.

$$\sigma(k_i, k_j)_{\lfloor K_j \in V_k} = \begin{cases} k_j \;\; \therefore \;\; K_j \in k_s - k, N_{K\alpha_j}^{K_i} \geq \sum_{j=1}^{m} N_{K\alpha_j}^{K_i} \\ Random\,(k_i, k_j), N_{K\alpha_j}^{K_i} < \sum_{j=1}^{m} N_{K\alpha_j}^{K_i} \end{cases} \qquad (4)$$

Next, changes in the interaction strength of the agents in the AgCom environment are considered based on the AgUser's route. The previous section introduced two parameters: (i) ***su*** that measured the extent to which AgUser is inclined to maintain his belief ***αi***, and (ii) ***sc*** that measured the influence the environment had over the AgCom's willingness to modify a belief ***αj***. The parameter $\eta = (sc / su) \in (0, 1)$ measured the relation between both terms, (i) if $\eta = 0$, the AgUser do not change his beliefs as a result of the interaction with the AgCom, and (ii) if $\eta = 1$, the AgUser estimates his own beliefs equal to those he receives from the environment. Under such conditions it is expected that the influence of the environment on the AgUser who initially had a belief ***αi***, to adopt a belief ***αj*** will be defined.

Then α_i^* is referred to as the value for AgUser belief ***αi*** , and α_i^n the value the agents AgCom attributes to that belief, where $n = 1,\ldots,N^k$. The influence needed to maintain the belief ***αi*** is determined by (5):

$$i_k(\propto_i) = s_u + \propto_i^* \sum_{n=1}^{N^k} s_c \,.\propto_i^n = s_u(1 + \propto_i^* \sum_{n=1}^{N^k} \eta \,.\propto_i^n) \qquad (5)$$

The results obtained and the initial conclusions on how to improve AgCom strategies for attracting greater numbers of clients.

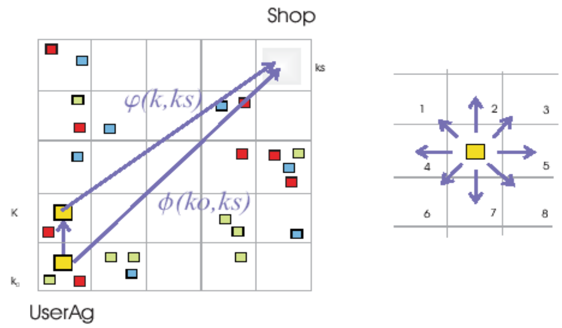

Fig. 1. (a) AgUser's movement in the shopping centre. (b) AgUser's possible movements

III. First Experiments with Agent Based Modelling Tools

In this section the first results obtained testing the previous mathematical model are showed. The analysis of these results enables to conclude ways to optimize the commercial strategies in three different experimental environments. A test-bed was used to find out the main features after checking several platforms in the field of agent based simulation. Those ones were: *NetLogo* [12], *MASON* [13,14], *Ascape* [15,16], *RePastS* [17,18], and *DIVAs* [19] given the fact that according to the literature, these are considered to be among the most effective platforms in the market [20]. After testing and reviewing the main features [21] (Environment structural complexity, Environment distribution, Agent and Environment coupling Specification offered by UI, Level of programming skill, Specified Environment knowledge in Agents, Quality of the visualization, Ease of change of properties of model and simulation view), our choice was NetLogo which enables the model simulation to be controlled by multiple users and distributed with respect to architecture and processing. NetLogo shows a very simple programming language to define, build and check models.

The following configurations were tested:

1) Commercial agents positioned near to the entrance. This strategy tries to persuade the user as soon as possible.
2) Commercial agents positioned close to area where the client pays for the product. This strategy tries to persuade the user when she/he is ready to pay.
3) Commercial agents situated across the diagonal D(A) and, therefore, with more chances to interact with the AgUser regardless of which route he/she does.

Each one of these environments corresponds to different strategies. For each of the configurations, it is monitored the evolution of parameter η of the AgUser (see previous section). The results can be seen in figure 2a, 2b and 2c.

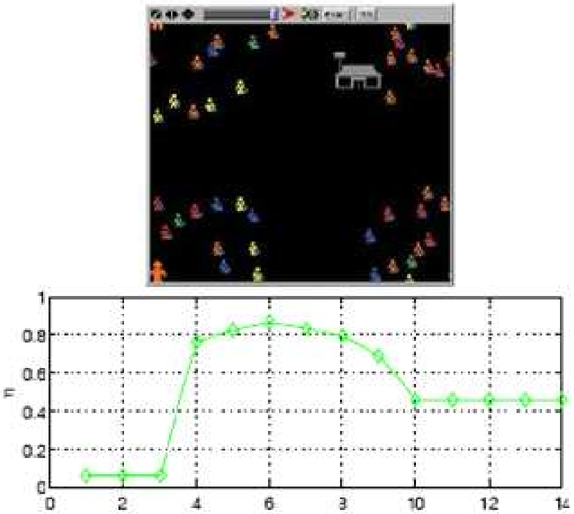

Fig. 2. (a). Commercial agents positioned near to the entrance

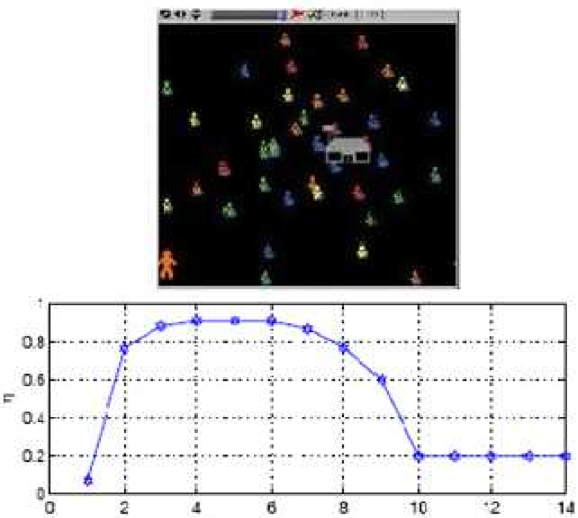

Fig. 2. (b). Commercial agents positioned close to the payment area

The results obtained seem to point to the following conclusions: the most useful strategy is related on distributions of agents able to interact with the UserAg *across the whole* way instead of waiting in strategic places.

In the next section some relevant issues related on the implementation of these models and strategies will be shown.

IV. Prototype and Implementation

The recommendation system in large shopping malls (RecMAS) is a computational tool based in MAS that attempts to convince clients to buy certain products. Each client, represented by an AgUser in a mobile device or PDA, interacts through a GPRS or wireless (Bluetooth or WiFi) connection with other agents in the shopping centre.

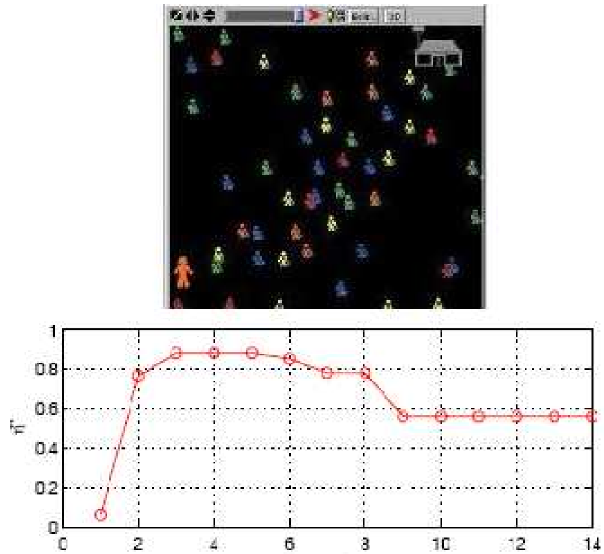

Fig. 2. (c). Commercial agents situated across the diagonal D(A)

Each store has *n* representatives (AgCom) distribted along the shopping centre with a scope limited to the sector *k* where they are located. From the point of view of implementation:

- The Gaia methodology [8] was used to model the multiagent system. It is comprised of role definition, protocols, services model, agents model and familiarity diagram. The Gaia methodology enables facile description of the agent system as an organization but has the inconvenience of not enabling a detailed level in the design stage. To correct this deficiency the modelling language Auml [9] was used. Auml is an extension of Uml (Unified Modeling Language) developed specially for agent (see figure 3 AgUser Class Diagram with AUML)
- Each agent has a deliberative architecture of the BDI sort implemented with a combination of its own platform and 3APL language [7]. 3APL (An Abstract Agent Programming Language) is a programming language for implementing cognitive agents. 3APL is based on a rich notion of agents, that is, agents have a mental state including beliefs and goals. 3APL language provides programming constructs for implementing agents' beliefs, goals, basic capabilities (such as belief updates, external actions, or communication actions) and a set of practical reasoning rules through which agents' goals can be updated or revised. The 3APL programs are executed on the 3APL platform. Each 3APL program is executed by means of an interpreter that deliberates on the cognitive attitudes of that agent.

As the AgUser's beliefs change after interaction with the AgComs in their coverage area, a procedure is defined for searching of nearby agents using a Bluetooth device. Figure 4 shows the deployment diagram application for mobile devices.

Some devices have experienced complications in sending/receiving processes when connecting via Bluetooth. In particular, Nokia 6620 and Nokia 6680 have worked successfully while the standard Bluetooth protocol JSR-82 has experienced inconsistent behavior. The reason appears to be due to the multiplicity of j2me versions with different restrictions on hardware.

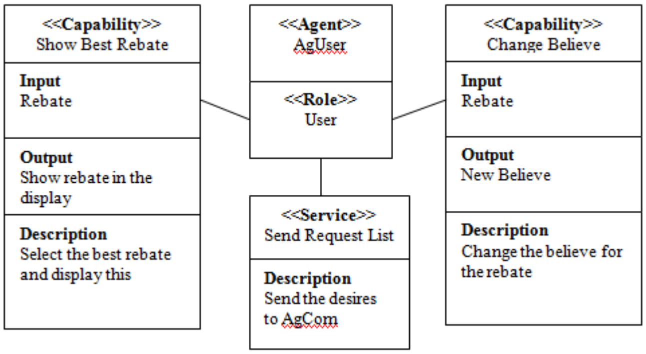

Fig. 3. AUML AgUser Class Diagram

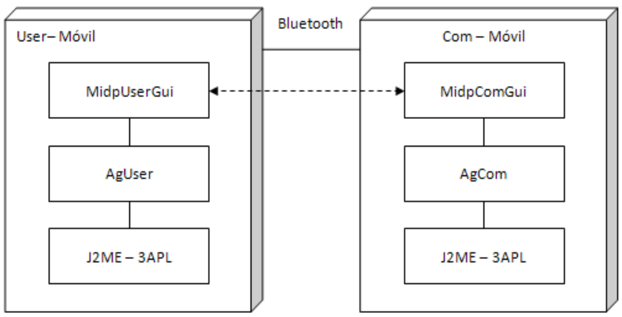

Fig. 4. Deployment Diagram for mobile device application

V. AGENTCOMS: TRADING KNOWLEDGE THROUGH LINKS

The following section seeks to optimize the interaction strategy of the AgCom, i.e., to calculate which percentage of AgComs move away from the diagonal or approach the beginning and end sectors, without decreasing the success level of the gradual strategy while attempting to attract the AgUser when it moves away from the diagonal path.

A. Complex optimization problem

From an analytical point of view complex *optimization problem* techniques and metrics should be used enabling characterization of a temporal AgCom distribution in two directions (*u, v*). It measures the AgComs' movement along the diagonal *D*(*A*) or anti-diagonal in the initial coordinates system (*x, y*) (See figure 5).

Movement inter-strategy: First, the progressive movement from a gradual strategy to environment type 2 and type 1 (Image 5A) are also calculated. The equations that determine such dynamics are determined by the following equations

$$\varphi_u^{(1)} = \frac{e^{\frac{-v^2}{2(\beta_0{}^2)}}}{2\,\pi\beta_0}\,\frac{e^{\frac{-u^2\,(1+\gamma t)^2}{2(\alpha_0)^2}}}{\alpha_0}(1+\,\gamma t)$$
$$\varphi_u^{(2)} = \frac{e^{\frac{-v^2}{2(\beta_0{}^2)}}}{2\,\pi\beta_0}\,\frac{e^{\frac{-(u-\frac{D(A)}{2})^2\,(1+\gamma t)^2}{2(\alpha_0)^2}}}{\alpha_0}(1+\,\gamma t) \qquad (6)$$

Where $\varphi_u^{(2)}$ reflects the case in which the distribution towards the shopping sector with coordinates (D(A)/2,0) is studied; α y β being adjustable parameters:

$$\propto\, = \frac{\propto_0}{(1+\gamma t)}, \beta\; = \beta_0 \qquad (7)$$

Spreading: Secondly, certain metrics are defined to characterize the level of AgCom distribution along the diagonal.

$$\varphi_v = \frac{e^{\frac{-u^2}{2(\propto_0{}^2)}}}{2\,\pi\alpha_0}\,\frac{e^{\frac{-v^2}{2(\beta_0-\gamma t)^2}}}{\beta_0+\gamma t} \qquad (8)$$

Optimization of these two functions requires consideration of a multiobjective function where optimization of the distribution of the number of agents is in the directions *u* and *v* from the diagonal. The problem is very complex and inefficient; therefore an optimization model will be proposed based on time adjustment of a number of the AgCom positions: substituting calculus and computational cost through a communication based adaptation plan, (see formula 9, figure 5).

$$\phi_x^{(1)} = \frac{e^{\frac{-y^2}{2\beta_0^2}}}{2\pi\beta_0}\,\frac{e^{\frac{-x^2}{2\alpha_0^2}(1+\gamma^t)^2}}{\alpha_0}\,(1+\gamma^t) \qquad (9)$$

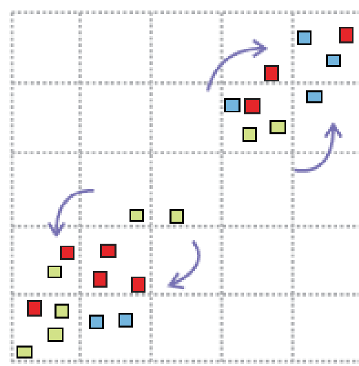

Fig. 5. Change of axis in the environment

B. Optimization using wireless communications

This section introduces a configuration model where rather than searching for a statistically successful static strategy, as in the previous example, the AgCom will follow simple coordination rules to adapt to AgUsers who are not following the diagonal. The proposed model shows how to find a dynamic adaptation to its environment in order to estimate if the AgUser is moving away from the diagonal route slightly or notably "as it goes". It is assumed that each AgUser can only communicate with other AgComs within their immediate environment. If the message sequence is constant, the distribution switches to the end sector (see figure 6(A)).

$$f_i(m+1)\;\propto\; f_{i-1}(m) + \gamma(u - \tfrac{D(A)}{2}) \qquad (9)$$

If the message sequence is intermittent “the agent is close to the diagonal” and the distribution opens the range of values (see figure 6(B)).

$$f_i(m+1) \propto f_{i-1}(m) + \gamma(v - \frac{D(A)}{2}) \qquad (10)$$

These simple rules force the AgComs to direct themselves towards (A), the shopping sector, or (B) to increase the range of their positions around the diagonal. The complexity of the communication relations based in these rules is not relevant (linear with regards to the number *N* of agents). The mobile devices are characterised by having less processing resources compared with computers. For this reason it was important to verify that the communication and search algorithms were not so complex that implementation would be impossible. A multithread routine was defined for the communication process that enabled interaction at a second level while information was presented to the user. One of the limitations of a Bluetooth Piconet is that it only supports up to 8 connected devices. In order to solve this restriction an JBAN library [10] was used enabling connection and control of an unlimited number N of devices in the network.

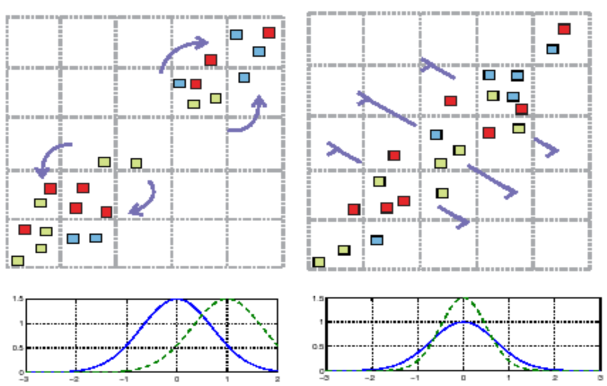

Fig. 6. Adaptation strategies: (A) Inter-strategy movement, (B) ”Spreading” of a gradual distribution

VI. Final Results: Strategies for the Adaptation in Real Time and the Dynamic Attraction of Clients

One of the aspects taken into consideration for the evaluation of results was to gradually increase the area of scope. Initially 8 subregions in the shopping centre were defined. All of them shared the same vertex (entrance of the user) and as the subregion was extended, it contained the previous region. The size ratio between one subregion and the next is based on 40 meters, thus, the smallest is that size and the largest is 8 times bigger (the enlargement is mainly horizontal, because this shopping centre is not square). Different valuations were undertaken (30 users, three times each). In each case the belief they had initially when they entered the shopping centre and the one they bought the product were evaluated (see figure 7). The evaluated strategies where the: (i) “Lying-in-wait” strategy (yellow in the graph), (ii) Gradual strategy (crimson in the graph) and (iii) Adaptive strategy (blue in the graph). These results were as follows:

1. “Lying-in-wait” strategy: For smaller environments the level of success is higher that in larger environments: on average the AgUser covers more space and has more interactions with other AgComs.
2. “Gradual” strategy: The level of success is higher than in the previous strategy for all the environments and decreases with the size in a trend similar to the previous case. Nevertheless, what is interesting about the result is that in relative terms the slope of the decrease of success falls more quickly.
3. “Adaptive” strategy: The most interesting result according to the gathered information is that the relative degree in which the success of the strategy decreases is much smaller than in the previous examples. In other words, the “adaptive” strategy is the only one that has acceptable results when the dimensions of the space considered is of a surface of 300 m2 or higher.

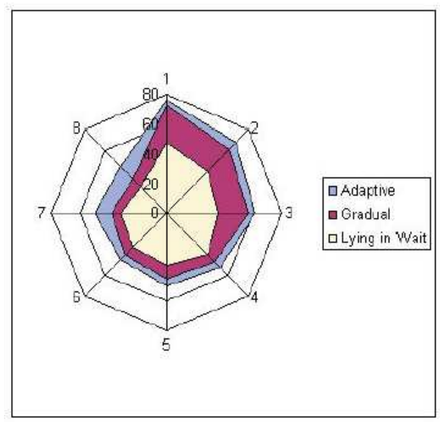

Fig. 7. Graphical representation of the level of the strategies’ success: (A) “Lying-in-wait” strategy, (B) Gradual strategy (C) Adaptive strategy.

A set of 1000 simulations were developed and data obtained are shown in the figure 8. The messages in the exchange protocol between AgComs are represented by JnMensajes and nMensajes when the protocol was measured by optimizing of complex problem.

	nMensajes	JnMensajes
Count	1000	1000
Average	5,984	16,149
Variance	6,97021	140,926
Standard deviation	2,64012	11,8712
Minimum	1,0	1,0
Maximum	10,0	40,0
Range	9,0	39,0

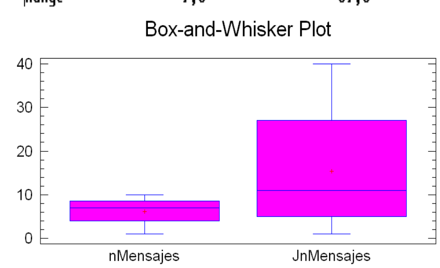

Fig. 8. (i) nMensajes in the optimizing problem and JnMensajes by TradeAgent protocol.

VII. CONCLUSIONS AND FUTURE WORK

A model of relations between an AgUser and AgComs inside a multiagent society was developed. This model was designed to represent the internal strength of an AgUser's beliefs and its resistance to belief change processes affecting the products it was predisposed to buying. Next, different environments were proposed representing different advertising strategies that the AgCom used in large areas. The tests, carried out in a real environment, helped to state the advantages one environment enjoyed with the help of wireless technology over another environment. A wireless system was provides to the system user, represented as an AgUser. The mobile device supported Bluetooth, GPRS and j2me. The AgCom had PDA devices that supported Bluetooth, j2me and WiFi. Initially each AgUser stored its user profile, where its initial preferences were identified, and initiated the shopping centre route, visiting stores while being informed of new offers. Once they finished their route, they went to a sector store and bought the product indicated by their beliefs. The evolution of AgUser beliefs was registered according to the interaction with the AgComs. The concluding part of the paper suggests that a dynamic search strategy be sought seeking AgUser interaction taking advantage of the possibilities provided by the use of mobile devices. The communication model based on proximity interaction relations avoids network overloads by the distribution of AgComs over the surface (compared with GPRS technologies that enable the communication and identification of the whole group of existing agents but whose interaction flux is more complex). The result has been very satisfactory: the local scope and the simple rules of interaction have enabled discovery of a strategy that evolves parallel to the AgUser's movement. The AgCom changed from occupying a static location that responded to a general strategy, to auto-organization based on the messages they receive from their nearest neighbours, anticipating the movements of the AgUser in relation to the diagonal.

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