Direct Marketing Based on a Distributed Intelligent System

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Abstract. Within a more globalized and inter-connected world, it becomes necessary to optimize resources for locating final products to target market segments. Direct Marketing has benefited from computational methods to model consumer preferences, and many companies are beginning to explore this strategy to interact with customers. Nevertheless, it is still an open problem how to formulate, distribute and apply surveys to clients, and then gather their responses to determine tendencies in customers' preferences. In this paper we propose a distributed intelligent system as a technological innovation in this subject. Our main goal is to reach final consumers and correlate preferences by using an approach that combines Fuzzy-C Means and the Analytic Hierarchy Process. A Multi Agent System is used to support the definition of survey parameters, the survey itself and the intelligent processing of clients' judgements. Clusters are synthesized after processing customers preferences and they represent a useful tool to analyze their preferences towards products' features.

Keywords: Direct Marketing, Fuzzy Clustering, Analytic Hierarchy Process, Multi Agent System.

1 Introduction

Many companies obtain feedback through surveys that are sent to potential customers either by regular or electronic mail. The current globalized and interconnected economy makes it compulsory to expend less energy, time and resources to drive the right products to the final consumers. Even though such forms of contact have been useful so far, the type of economy that surges in an interconnected world demands the interaction of business systems analysts, database developers, statisticians, graphic designers and client service professionals [1].

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tact have been useful so far, the type of economy that surges in an interconnected world demands the interaction of business systems analysts, database developers, statisticians, graphic designers and client service professionals [1].

More companies are exploring strategies such as Costumer Relationship Management or Direct Marketing for reducing costs and increase profitability by acquiring information directly from data sources. A recent survey indicates that the following issues are the top three executive concerns: Customer satisfaction, customer retention, and marketing return of investment. This is so because they are undoubtedly critical to current rapidly evolving marketing tactics: Web 2.0 (19.4 percent), Social Networking (12.2 percent), and Social Media (11.3 percent) (Cf. [2]). Given the fact that Information Technologies (IT) are playing a major role to interact with clients, customer-specific information can be collected and used for analyzing markets, and drive promotion campaigns based on such analysis [3].

Many techniques have been applied to select target markets in commercial applications, such as statistical regression [4], regression trees [5], neuronal computing, [6, 7], fuzzy clustering and the called Recency, Frequency, and Monetary Value (RMF) variable [8, 9, 10]. On the other hand, Web sites in combination with IT's have become an appealing and world-wide media to final users: When all pretense of limiting commercial use was removed in 1995 when the National Science Foundation ended its sponsorship of the Internet backbone, marketers employed this powerful medium, and Internet commerce was born [11]. The impact of electronic markets on a firm's product and marketing strategies have been examined empirically by [12] and [13]. The impact on price of reduced buyer search cost, allocation efficiency, and different incentives to invest in electronic markets are examined in [14]. In [15] it is analyzed the competition between conventional retailers and direct marketers. Even though such techniques have been valid, paradigms such as Multi-Agent Systems (MAS) and clustering provide useful techniques to improve business intelligence by facilitating management interaction with customers subjective judgements.

Therefore, we explore the combination of soft-computing algorithms to interact with clients. We propose the usage of MAS, the Analytic Hierarchy Process (AHP) [16] and the Fuzzy C-Means ([17]) to define survey's parameters, distribute such criteria to point sales, gather customers judgements, and obtain the pattern of clients' preferences.

More specifically, our system consists of the following modules. The module that is used to define survey's criteria resides at the management's site. It is also employed to publicize the survey to point-sales. Point-sales, which are located in different regions, possess an evaluation module that helps collecting customers' judgements on an evaluation sheet. Raw data is stored in an evaluation blackboard residing at the management side. A third module is in charge of processing the evaluations provided by customers. The processing of raw data is carried by combining Fuzzy C-Means and the AHP. Fuzzy C-Means contributes with a classification of similar families of customers, while the AHP offers the final ranking of products based of the clusters that are synthesized. Altogether, the distributed and intelligent system that we proposed is useful to elucidate the patterns associated with a given market segment.

This paper has the following structure. In Section 2, we delineate broadly how to integrate the Analytic Hierarchy Process and the Fuzzy C-Means to Direct Marketing. Section 3 formally describes the AHP, Fuzzy C-Means and the algorithm we developed to merge both techniques. Section 4 describes the Distributed Intelligent System structure and dynamics. Experimental results are depicted in Section 5. Finally, conclusions and future work are presented in Section 6.

2 Formation of clusters to boost direct marketing

As we stated previously, one major issue related to direct marketing is how to process a (normally large) number of clients' evaluations of products. The Analytical Hierarchy Process (AHP) ([16]) is employed for ranking a finite set of m alternatives, which are evaluated (subjectively) over a finite set of p evaluation criteria.

The AHP is suitable for processing surveys because, on the one hand, it allows management to define what set of products are to be evaluated along with the set of evaluation criteria. However, the AHP was originally devised for individual judgements. When it comes to be used as a tool for group decision making, it surges the question of how to process every individual evaluation. Our solution is explained next.

When the size of a market segment is established, customers are required to complete the evaluation sheet of the system we developed. Such evaluation complies to the structure of the AHP. That is to say, each client must evaluate a set of the company products (alternatives) by judging their relevant features (criteria). So far, so good. Nevertheless, management confronts a large number of raw data in order to elucidate how the company products are evaluated by the given market segment.

Let us suppose the market segment consists of z individuals. A matrix can be formed in order to compare criteria on a pairwise basis, as evaluated by each individual. This matrix is called Pairwise Comparison Matrix (**PCM**). Therefore, management will be forced to process z **PCM**'s. More specifically, all such matrices must be treated mathematically to obtain a value that truly reflects the likes and dislikes of the market segment.

The Fuzzy C-Means algorithm (FCM) is then applied to values of the **PCM** in order to define the largest cluster and its corresponding centroid. Thus, FCM yields a centroid for each entry of **PCM**, representing the most preferred value (tendency) of the group. Each global value is entered to the Global Pairwise Comparison Matrix **PCM**^{G}. When matrix **PCM**^{G} is completed, the AHP is executed as if the group were a single evaluator.

Consequently, grouping individual judgements gives management a solid knowledge regarding how the target market segment perceives the company products.

3 Formal presentation of methods

3.1 The Analytical Hierarchy Process

It consists of three major stages. First, an evaluator judges the relative importance of evaluation criteria on a pair-wise basis. This leads to a Pairwise Comparison Matrix (**PCM**), possessing the following structure:

$$\mathbf{PCM} = \begin{vmatrix} 1 & c_{12} & \dots & c_{1p} \\ c_{21} & 1 & \dots & c_{2p} \\ \vdots & \vdots & \vdots & \vdots \\ c_{p1} & c_{p2} & \dots & 1 \end{vmatrix}, \tag{1}$$

where c_{ij} is a numeric value that shows the relative importance of criterion c_i to criterion c_j. This first stage completes with the calculation of the eigenvector of the **PCM**.

$$\mathbf{eigenCriteria} = \begin{vmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{vmatrix}, \tag{2}$$

Eigenvector **eigenCriteria** defines the actual priority obtained by each criterion. On a second stage, the evaluator decides to what extent one alternative over another complies with a given criteria.

$$\mathbf{PCM}_{\mathbf{alternative}}^{\mathbf{criterion}} = \begin{vmatrix} 1 & a_{12} & \dots & a_{1m} \\ a_{21} & 1 & \dots & a_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \dots & 1 \end{vmatrix}, \tag{3}$$

where a_{ij} is a numeric evaluation that reflects to what extent alternative a_i complies with criterion c_k when compared to alternative a_j. The eigenvector of matrix 3 is computed.

$$\mathbf{eigenAC_k} = \begin{vmatrix} eac_{1k} \\ eac_{2k} \\ \vdots \\ eac_{mk} \end{vmatrix}, \tag{4}$$

In **eigenAC$_\mathbf{k}$**, eac_{jk} represents how alternative j ranks when it is evaluated against criterion k. The second step is repeated as many times as criteria exist, terminating when all the resultant eigenvectors are arranged orderly in matrix **EIGENAC**. The third and final step of the AHP consists of multiplying matrix **EIGENAC** times eigenvector **eigenCriteria** calculated in step one.

$$\mathbf{EIGENAC} \cdot \mathbf{eigenCriteria} \tag{5}$$

The result is vector **W**:

$$\mathbf{W} = \begin{vmatrix} w_1 \\ w_2 \\ \vdots \\ w_m \end{vmatrix}, \tag{6}$$

where w_l represents the final and definite ranking obtained by each alternative. The alternative with the highest score gets the highest rank.

3.2 Fuzzy C Means Clustering Algorithm

Data clustering is concerned with the partitioning of a data set into several groups such that the similarity within a group is larger than among groups. This implies that the data set to be partitioned has to have an inherent grouping to some extent; otherwise if the data is uniformly distributed, trying to find clusters will fail, or will lead to artificially introduced partitions. Another problem that may arise is the overlapping of data groups. Overlapping groupings sometimes reduce the efficiency of the clustering method, and this reduction is proportional to the amount of overlap between groupings.

The approach of the clustering technique here presented is to find cluster centers that will represent each cluster. A cluster center is a way to tell where the heart of each cluster is located, so when presented with an input vector, the system can tell to which cluster such vector belongs by measuring a similarity metric between the input vector and all the cluster centers, and determining which cluster is the nearest or most similar one.

In the following, the well-known Fuzzy C- Means Clustering algorithm is shown ([17]). Fuzzy C-means clustering (FCM), relies on the basic idea of Hard C-means clustering (HCM) [17]. Bezdek proposed this algorithm in 1973 [18], with the difference that in FCM each data point belongs to a cluster to a degree of membership grade, while in HCM every data point either belongs to a certain cluster or not.

So FCM employs fuzzy partitioning such that a given data point can belong to several groups with the degree of belongingness specified by membership grades between 0 and 1.

Let us define a set of n vectors, x_i, $i = 1, \ldots, n$ are to be partitioned into c fuzzy groups G_i, $i = 1, \ldots, c$, and find a cluster center on each group such that a cost function of dissimilarity measure is minimized. Imposing normalization stipulates that the summation of degrees of belongingness for a data set always be equal to unity:

$$\sum_{i=1}^{c} \mu_{ij} = 1, \quad \forall \; j = 1, \ldots, n. \tag{7}$$

The cost function (or objective function) measures a fuzzy distance between a vector x_k in group j and the corresponding cluster center c_i, can be defined by:

$$J(U, c_1, c_2, \ldots, c_c) = \sum_{i=1}^{c} \sum_{j=1}^{n} (\mu_{ij})^m d_{ij}^2, \tag{8}$$

where μ_{ij} is between 0 and 1, c_i es the cluster center of fuzzy group i, $d_{ij} = ||c_i - x_j||$ is the Euclidean distance between ith clusters center and jth data point; and $m > 1$, is called a weighted exponent, which is judiciously chosen. Observe matrix U being defined by an $c \times n$ membership matrix, where the element $\mu_{ij} \in [0, 1]$ is defined by a membership function for the jth data point x_j belonging to group i, as:

$$\mu_{ij} = \begin{cases} 1 & if \; ||x_j - c_i||^2 \leq ||x_j - c_k||^2, \; \text{for each} \; k \neq i, \\ 0 & , \; \text{otherwise} \end{cases} \tag{9}$$

The necessary conditions for Eq. (8) to reach a minimum can be found by forming a new objective function *barJ* as follows:

$$\begin{aligned} \bar{J}(U, c_1, c_2, \ldots, c_c, \quad \lambda_1, \ldots, \lambda_n) &= \\ &= J(U, c_1, c_2, \ldots, c_c) + \sum_{j=1}^{n} \lambda_j (\sum_{i=1}^{c} \mu_{ij} - 1) \\ &= \sum_{i=1}^{c} \sum_{j=1}^{n} \mu_{ij}^m d_{ij}^2 + \sum_{j=1}^{n} \lambda_j (\sum_{i=1}^{c} \mu_{ij} - 1), \end{aligned} \tag{10}$$

where λ_j, $j = 1$ to n, are the Lagrange multipliers for the n constraints in Eq. (7). By differentiating $\bar{J}(U, c_1, c_2, \ldots, c_c, \lambda_1, \ldots, \lambda_n)$ with respect to all its input arguments, the necessary conditions for Eq. (8) to reach its minimum are

$$c_i = \frac{\sum_{j=1}^{n} \mu_{ij}^m x_{ij}}{\sum_{j=1}^{n} \mu_{ij}^m}, \tag{11}$$

and

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\frac{d_{ij}}{d_{kj}}\right)^{\frac{2}{m-1}}}, \tag{12}$$

In the following, the clustering algorithm is stated.

Algorithm 1 (Fuzzy C Means). Given the data set Z, choose the number of cluster $1 < c < N$, the weighting exponent $m > 1$, a constant for a cost function minimum $\varepsilon > 0$, and a constant Th which is a termination tolerance threshold. Initialize the

partition matrix U randomly, such that $\mu_{ij}(0) \in [0,1]$

Step 1. Compute clusters prototypes: Calculate c fuzzy cluster centers c_i, $i = 1 \ldots, c$ using Eq. (11).

Step 2. Compute the cost function According to Eq. (8). Stop if either it below the tolerance ε or its improvement over previous iteration is below the threshold Th.
Step 3. Compute a new U using Eq. 12. Go to **Step 2.**
End of the FC-Means algorithm

3.3 The hybrid approach to process customers evaluations

We describe the usage of Fuzzy C-Means and the AHP to process customers' judgements. The combined usage of Fuzzy C-Means and the AHP to Direct Marketing is explained next.

Let $\xi = \{e_1, e_2 \cdots, e_n\}$ be the set of clients' evaluations, each of whom must compare the relative importance of a finite set of criteria $C = \{c_1, c_2, \cdots, c_p\}$ on which products are judged. This results in:

$$\mathbf{PCM^k} = \begin{vmatrix} 1 & a_{12}^k & \ldots & a_{1p}^k \\ a_{21}^k & 1 & \ldots & a_{2p}^k \\ \vdots & \vdots & \vdots & \vdots \\ a_{p1}^k & a_{p2}^k & \ldots & 1 \end{vmatrix}, \tag{13}$$

where $k = 1, 2, \cdots, n$ is the k_{th} client's evaluation; a_{ij}^k is the relative importance of criterion i over criterion j as determined by client's evaluation e_k.

When all the n Pairwise Comparison Matrices are formed, it remains to construct matrix $\mathbf{PCM^G}$ that reflects the pattern associated with the totality of the clients' evaluations.

The algorithm to construct the Global Pairwise Comparison Matrix is as follows.

1. The cardinality p of set C is computed.
2. A matrix $\mathbf{PCM^G}$ of dimensions $p \times p$ is formed.
3. The diagonal of matrix $\mathbf{PCM^G}$ is filled with 1.
4. Vector α_{ij} is formed with entries $a_{ij}^k, k = 1, 2, \cdots, n$.
5. $a_{ij}^G = FuzzyCMeans(\alpha_{ij})$
6. Method *countIncidences* is called for determining the quantity of evaluators inside each cluster. Cluster with the highest number of incidences is selected. Cluster centroid is obtained.
7. Repeat steps 4, 5, 6 $\forall (i, j) = 1, 2, \cdots, p; \forall (PCM^k), k = 1, 2, \cdots, n$

Thus,

$$\mathbf{PCM^G} = \begin{vmatrix} 1 & a_{12}^G & \dots & a_{1p}^G \\ a_{21}^G & 1 & \dots & a_{2p}^G \\ \vdots & \vdots & \vdots & \vdots \\ a_{p1}^G & a_{p2}^G & \dots & 1 \end{vmatrix}. \tag{14}$$

Equation (14) is the resultant Global Pairwise Comparison Matrix that serves as basis to execute the AHP once all the customers's evaluations are processed.

Next, we illustrate how a Multi-Agent System fully automates the processing of data. Specifically, the entire set of activities, from data gathering, processing and final calculation is performed by the distributed and intelligent multi-agent system.

4 The Multi-Agent System

This section depicts the Multi-Agent System structure and dynamics. The MAS is fixed by the following agents, whose structure is shown in Fig. (1) by means of a deployment diagram:

- A *coordinator agent*,
- A set of *evaluator agents*,
- A *clustering agent*,
- An *AHP agent*.

These agents altogether posses the following dynamics:

1. The *coordinator agent* acquires problem variables i.e. the set of criteria associated to the survey, the set of products to be evaluated, as well as the number of clients that will perform the evaluation. It leaves a message on the *Evaluation Blackboard* to inform each of the *evaluator agents* about the newly input survey.
2. Each of the *evaluator agents* assists in the evaluation of criteria and products, as each client provides his/her judgement.
3. The *coordinator agent* corroborates that every *evaluator agent* has completed its task, by querying the *Evaluation Blackboard*.
4. The *coordinator agent* informs *clustering agent* upon verification of data completeness. Then, *clustering agent* processes clients's evaluation with Fuzzy C-Means to build clusters.
5. The *clustering agent* informs the *coordinator agent* upon completion of its assignment.
6. The *coordinator agent* request the *AHP agent* to compute the final prioritization of products by running the AHP. Then, it informs when the task is achieved.
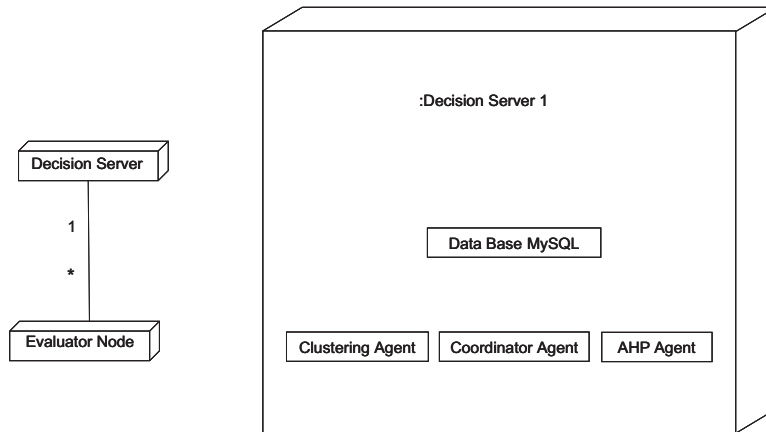
Fig. 1 Structure of the Multi-Agent System.

The previous list of activities is formally represented in the communication diagram of Figure (2). Those two types of diagrams are part of UML 2.0 [19].
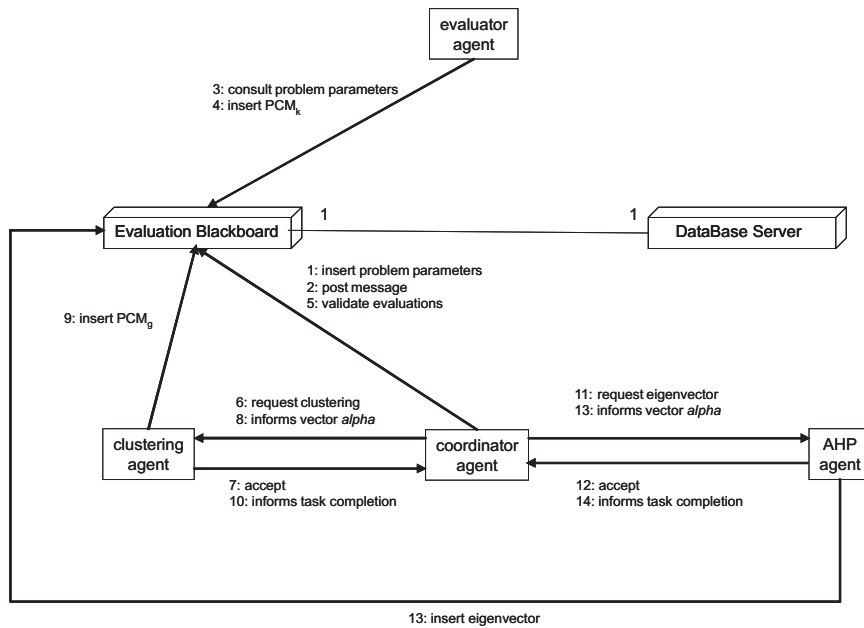
Fig. 2 Communication diagram of the Multi-Agent System

The implementation of the MAS is done on the JADE platform [20]. JADE is a useful tool because it allows to promote intelligent behavior to a given agent, while

providing a rich set of communication capabilities based on FIPA-ACL. Both, the Fuzzy C-Means clustering technique and the AHP were developed on Java so *clustering agent* and *AHP agent*, respectively, call the coding transparently. The MAS is a distributed architecture because each agent resides in its own processing unit, and communication is done over the TCP/IP protocol, for which JADE possesses powerful libraries.

As it can be seen in Fig. (1), the *coordinator agent* communicates directly with both, the *clustering agent* and the *AHP agent*. It is not so regarding the *evaluator agents*. In this latter case, communication is done by posting messages on the *Evaluation Blackboard*. This *Evaluation Blackboard* is represented in Fig. (2) as an *artifact*. Such blackboard is actually a database implemented on MySQL, whose structure is shown in Fig. (3).
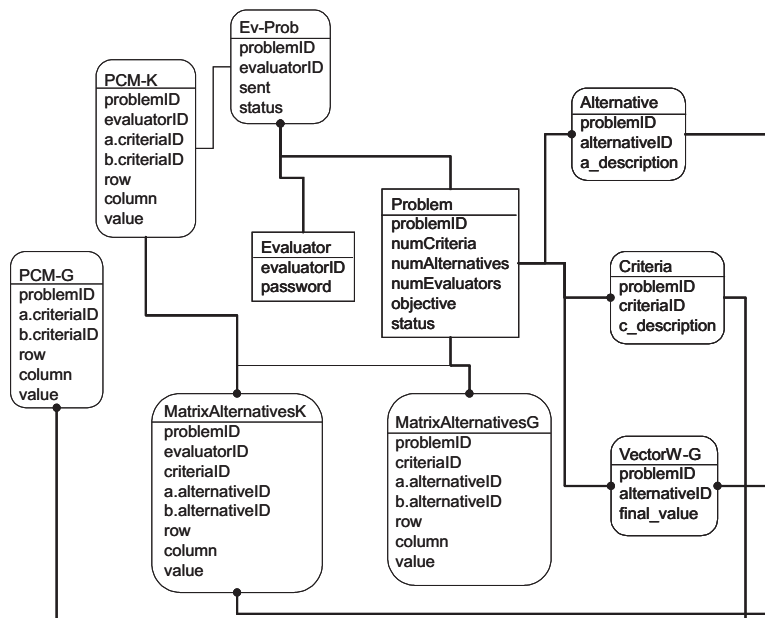

Fig. 3 IDEF1x model of the Evaluation Blackboard.

Being the MAS a distributed architecture, it results a very useful tool for modern organizations because management and point sales are geographically separate entities. However, they must share the same information in order to achieve direct marketing. At this regard, management defines the set of criteria to evaluate products, what products must be evaluated, and the size of the population that will provide judgements. This is done at one physical location. The *coordinator agent* assists management directly.

On the other hand, actual salesmen or women are in touch with clients, yet they must adhere to the criteria fixed by management. The *evaluator agent* is running

inside the computer used by the sales force, and gathers the criteria that was decided by management. There is one *evaluator agent* assisting every salesman or woman regardless their actual location. This is helpful to interview the clients they talk to. In this way, the clients opinions are fed to the central repository in real time.

When the totality of opinions are input, the *coordinator agent* orders the *clutering agent* and the *AHP agent* to process clients' data so management can visualize the manner in which a given market segment judges the company's products.

Such tasks are exemplified in section 5.

5 Experimental results

In this section we present a case-study to validate the combined Fuzzy C-Means - AHP -MAS approach to direct marketing. The case study refers at determining what car model out of a list is best judged by a number of potential clients belonging to a specific market segment. To show the validity of the approach, we only provide data given by ten different clients, whom were asked to judge five different cars models on five different criteria. Management and salesmen or women were asked to employ the MAS. We present, step by step, the usage of the MAS and the final results.
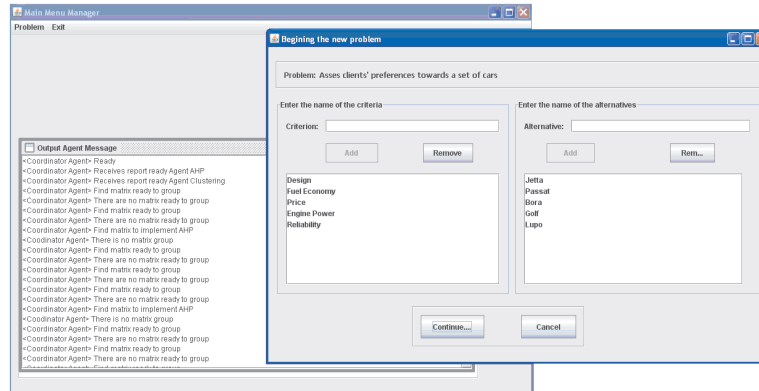

Fig. 4 Coordinator Agent. Entering survey parameters.

Let $\xi = \{e_1, e_2, \cdots, e_{10}\}$ be the set of clients, and $C = \{c_1, c_2, c_3, c_4, c_5\}$ the set of criteria where: c_1 = Design, c_2 = Fuel Economy, c_3 = Price, c_4 = Engine Power, and c_5 = Reliability. Five different alternatives are evaluated, which are labeled A_1 = Jetta, A_2 = Passat, A_3 = Bora, A_4 = Golf, and A_5 = Lupo.

Management, comfortably sitting in their headquarters, introduce the survey parameters in a Graphical User Interface associated to the *coordinator agent*. Firstly, they establish the ID associated with the problem, along with the number of criteria,

alternatives and population size (total number of evaluators). Afterwards, they introduce the objective of the problem, description of criteria, and the products to be evaluated (Fig. 4). These parameters are stored in Table *Problem* of the *Evaluation Blackboard* previously described. Accordingly, Fig. (5) displays the final definition of the survey parameters.
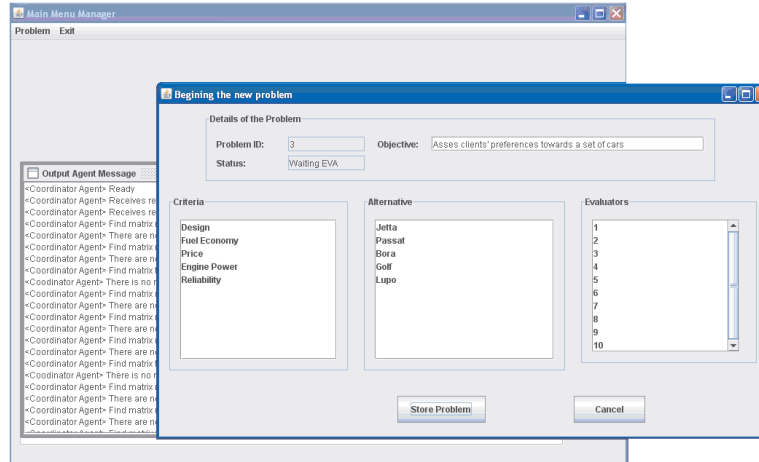

Fig. 5 Coordinator Agent. Summary of survey parameters.

Once the problem parameters are introduced, the *coordinator agent* posts a message on the *Evaluation Blackboard*, which will be read by each of the *evaluator agents* on their own network location. Thus, each *evaluator agent* constantly verifies whether a new problem has been introduced.

When a new survey is encountered (Fig. 6), its parameters are displayed so that the evaluator proceeds to determine the absolute importance of every criterion (Fig. 7).

Here we would like to elaborate on this way of evaluation. According to empirical usage of the system, human evaluators complaint about the time consuming process and the inability to keep track of their own judgements when they were requested to pair-wise compare both, criteria and alternatives. They also expressed that the numbers they were facing lacked meaning at some point. Instead, all of them agreed that it is more intuitive to make an absolute judgement on a 1-10 scale, and automate the pairwise comparisons as part of the system. The construction of the pair-wise comparison matrix for criteria is transparent to the evaluator. It also guarantees consistency of the PCM. Consequently, this process yields a PCM matrix for each evaluator, which is stored in the table *PCM-K* of the *Evaluation Blackboard*.

Upon completion of the entire set of evaluations, the *coordinator agent* informs the *clustering agent* that it must initiate the calculation of the clusters (Fig. 8).

Then, *clustering agent* acknowledges receipt and proceeds to build clusters, and then stores the Global PCM in table *PCM-G* of the *Evaluation Blackboard*. A sum-
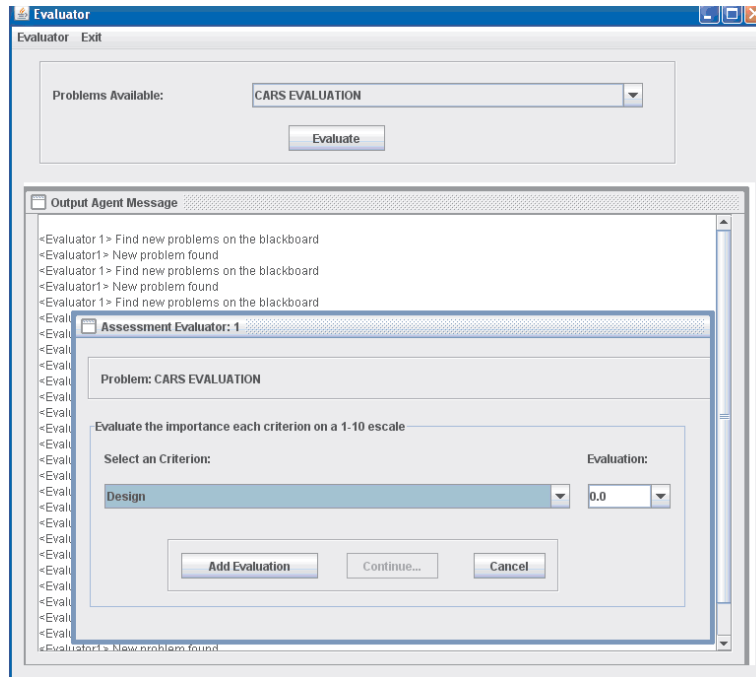
Fig. 6 Evaluator Agent. Finding a new survey at Sales Point.

mary of the final results for this particular case are displayed in Fig. (9), while the details can be analyzed as presented in Fig. (10).

5.1 Clients' evaluation.

The actual judgements given by the clients are depicted in the following table. First, they were asked to evaluate on a scale from 0 to 10, how important is Design (c_1), Fuel economy (c_2), Price (c_3), Engine power (c_4), and Reliability (c_5) at the moment of selecting a car.

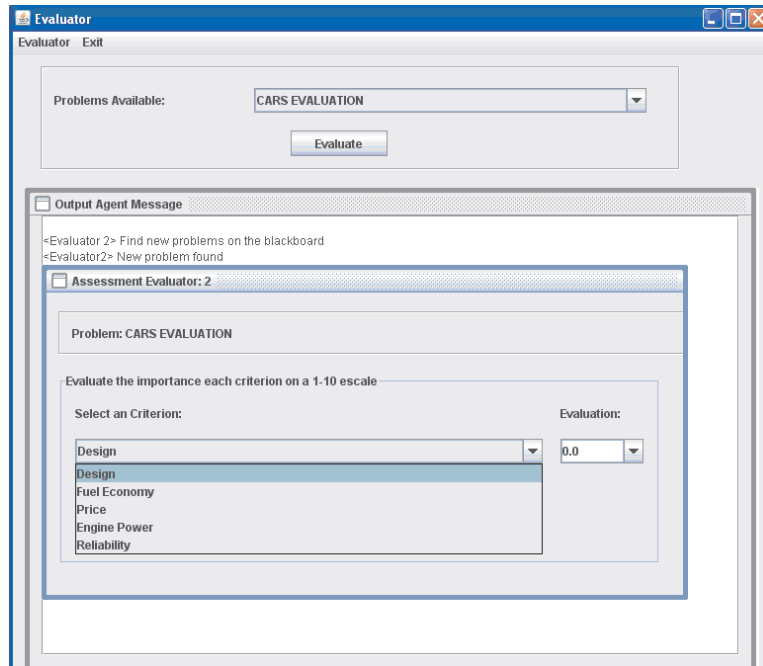| c_i	e_k									
	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9	e_{10}
c_1	8	9	9	9	10	7	7	6	10	7
c_2	9	8	9	7	6	8	9	9	7	8
c_3	10	10	8	9	7	10	6	10	6	8
c_4	10	9	8	7	8	6	10	6	10	6
c_5	8	8	9	8	7	6	8	10	8	7

Fig. 7 Evaluator Agent. Criterion evaluation.
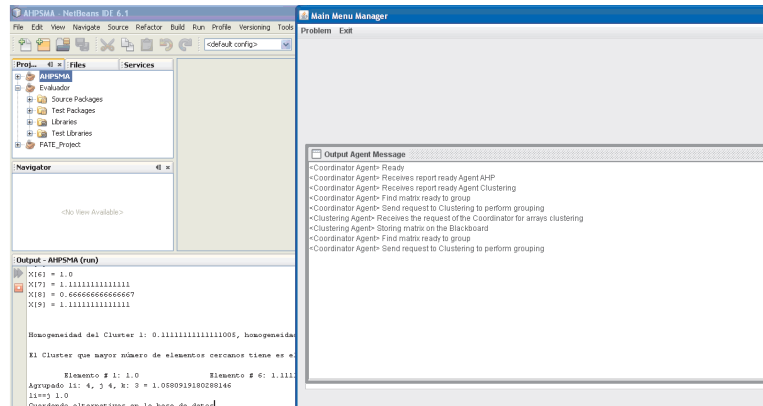

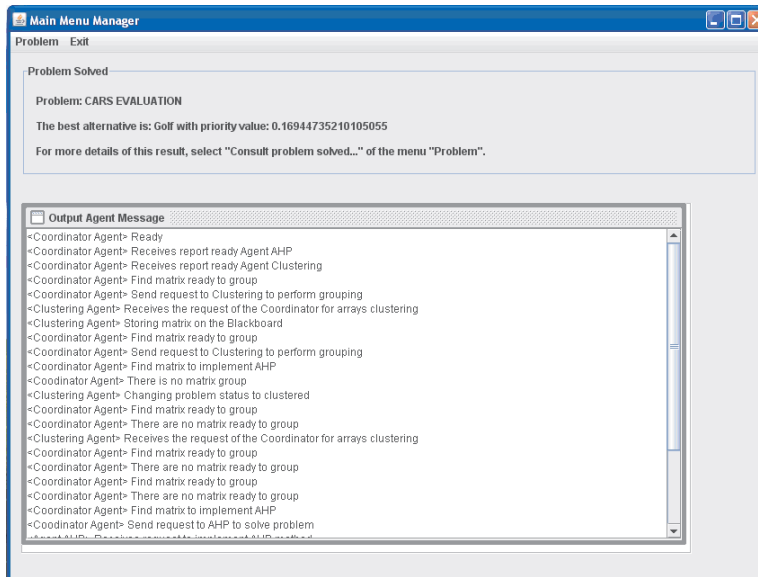**Fig. 8** Coordinator Agent informs Clustering Agent.

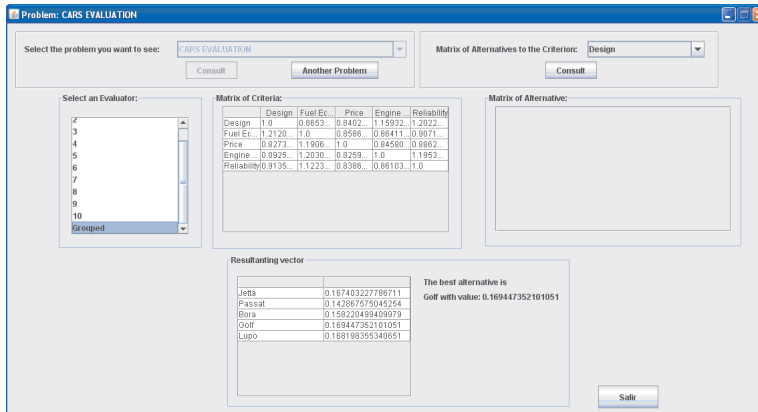**Fig. 9** Summary of final results

Fig. 10 Details of final results

Once every client has established how important every criteria he/she considers to be in for purchasing a car, clients are asked to evaluate to what extend they think alternative cars comply to the evaluation criteria. In the following table we present only one example of how one client ranked the five different car models on each criteria.

e_1	a_i				
	Jetta	Passat	Bora	Golf	Lupo
c_1	8	10	10	8	6
c_2	9	4	5	8	10
c_3	7	4	6	7	10
c_4	8	10	9	8	5
c_5	9	10	10	8	8

According to the previous table, client number one considers that *Jetta* evaluates with an 8 for its design, a 9 for its fuel economy, 7 for the price, 8 for the engine power, and a 9 for the reliability. There is one instance of the previous table for every one of the clients that participate in the survey. The totality of the evaluations are stored in the the *Evaluation Blackboard* (Fig. 3).

Once the target population evaluated (subjectively) the range of products, then the *coordinator agent*, running on the management node, validates that all the evaluations are complete. Shortly after, it requests that *clustering agent* and *AHP agent* achieve their own tasks by processing the raw data.

Knowledge obtained by management is a final ranking, which determines what product appeals the most to the target market segment. In this case, A_4 = Golf best balances the five features evaluated, as evidenced by ranking $R = \{A_1 : 0.1674, A_2 : 0.1428, A_3 : 0.1582, A_4 : 0.1684, A_5 : 0.1681\}$.

6 Concluding Remarks

We have presented an intelligent and distributed Multi-Agent System that incorporates the Analytical Hierarchy Process and the Fuzzy C-Means algorithm to enhance direct marketing. Particularly, the system is aimed at facilitating surveys and processing the large amounts of raw data that is generated.

The results provided with the case-study are very promising, because it has been shown that management can establish direct contact with a large group of customers. Every individual, in turn, is left free to evaluate the company products according to his or her personal criteria.

This is very valuable per se. Yet, the system also proved capable of processing the totality of the evaluations. With this, the perceptions of a market segment are deeply scrutinized by forming clusters. In this sense, the market segment is treated as a single unit because the perceptions of the majority are discovered.

It is intended to improve the MAS we have presented here by including different soft-computing techniques, such as neural networks and Case-Based reasoning. These techniques will provide more facilities so that management can compare and analyze the market behavior.

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