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Multi-Agent Based Modeling Using Multi-Criteria Decision Analysis and OLAP System for Decision Support Problems

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***Abstract*—**This paper discusses the intake of combining multi-criteria decision analysis (MCDA) with OLAP systems, to generate an integrated analysis process dealing with complex multi-criteria decision-making situations. In this context, a multi-agent modeling is presented for decision support systems by combining multi-criteria decision analysis (MCDA) with OLAP systems. The proposed modeling which consists in performing the multi-agent system (MAS) architecture, procedure and protocol of the negotiation model is elaborated as a decision support tool for complex decision-making environments. Our objective is to take advantage from the multi-agent system which distributes resources and computational capabilities across interconnected agents, and provide a problem modeling in terms of autonomous interacting component-agents. Thus, the identification and evaluation of criteria as well as the evaluation and ranking of alternatives in a decision support situation will be performed by organizing tasks and user preferences between different agents in order to reach the right decision. At the end, an illustrative example is conducted to demonstrate the function and effectiveness of our MAS modeling.

***Keywords*—**Multidimensional Analysis, OLAP Analysis, Multi-criteria Decision Analysis, Multi-Agent System, Decision Support System.

I. Introduction

RECENTLY, decision support systems have been largely improved thanks to a large number of scientific researches. OLAP tools, being a decision making technology, appear as a complete system that provides helpful and necessary services for a rational and efficient treatment of intelligence data. In this kind of models, the data are well organized multi-dimensionally so that the decision makers could analyze them interactively and iteratively at a detailed and/or aggregated level. However, in multi-criteria decision-making situations, OLAP has some shortcomings due to the complexity problems arising from the presence of more than one criterion during the data analysis process, and from the lack of structuring complex situations requiring a huge number of qualitative and quantitative data, which lead to failure in achieving decision quality improvement and low decision makers' satisfaction. It is therefore natural to consider different types of data (more criteria) in the design of OLAP cubes by integrating other analytical paradigms such as multi-criteria analysis in the final process of OLAP analysis. In fact, multi-criteria decision analysis (MCDA) can provide tools for the decision makers enabling them to progress in solving a decision-making problem where various conflicting viewpoints should be taken into consideration. This will enable us to consider the multi-criteria and qualitative aspects of data, and then reduce the degree of uncertainty and imprecision throughout the analysis process. In this context, understanding the internal operations of this combination involves making a functional modeling by explaining the intervention of each element composing this combination, which will make the tasks of these elements automatic within the final system. The multi-agent systems (MAS) as a novel modeling of business automation, are being increasingly used in many application areas, especially for their ability to design, model and implement software systems [1], [2]. It can be defined as a computerized system consisting of multiple interacting agents that operate collectively within an environment through cooperation or competition [3]. Also, a MAS can be used to solve problems that are difficult for the capabilities of an individual agent. For example, in complex environments, MAS can bring faster and more effective methods of resource allocation such as the utility networks management, compared to any human-centered approach. Moreover, in relation to our contribution, MAS distributes computational capabilities and resources across interconnected agents, and provides a problem modeling in terms of autonomous interacting component-agents, which can be a natural way of representing team planning, task allocation, user preferences... etc.

MAS technology is currently being developed for a variety of applications including condition monitoring [4], [5], diagnostics [6], hybrid control [7], airport ground handling management [8], integrated emergency vehicle dispatching problem [9], energy management strategy [10] and dynamic real time rescheduling and learning [11]. These MAS applications cover diverse domains such as wireless collaborations and communications, supply-chain management, financial portfolio management and electronic book buying coalitions etc. Concerning the MAS application in decision-making field, which is the scope of our study, we cite as example the contribution of [12] in which the authors propose to develop multidimensional academic information networks with a novel data cube based modeling method, and use a multi-agent based algorithm to extract knowledge with low running time and high accuracy from such very huge information networks. Also, [13] suggests a new methodology

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based on learning techniques for a web-based multi-agent-based application (web usage mining) to discover the hidden patterns in the user's visited links. The authors have presented a new approach involving cooperation and reinforcement learning among agents to find out patterns representing the profiles of the user in a sample website into specific categories of materials, through the use of significance percentages. Cao et al. [14] propose to develop a multi-strategy negotiating agent system for e-commerce decision making by formally defining the agent's conceptual model, and designing its abstract architecture which is integrated with contract net protocol.

Several other studies have implemented MAS and its architecture of the negotiation model in their contributions such as [15]-[18]. Moreover, applying MAS for decision support system is also addressed in many studies such as [19]-[23]. However, conducting a multi-agent modeling for the integration of multi-criteria decision-making analysis within OLAP system has attracted little attention, especially for decision support problems. Thus, the objective of this paper consists in presenting a multi-agent system-based modeling for decision support system by combining multi-criteria decision analysis (MCDA) with OLAP system. This will allow us to take into consideration different aspects of data (quantitative, qualitative and multi-criteria aspects) during the analysis process. Also, the proposed modeling will enable decision makers to face several decision making problems, especially, complex problems evolving in time by taking advantage from the analytic flexibility that OLAP system can provide.

The remainder of this paper is organized as follows: in Section II, the proposed multi-agent modeling is presented. Section III presents a clear description of the algorithm and analysis involved to perform the proposed multi-agent system. Section IV discusses the results of applying our multi-agent modeling for an example of decision support problem. We end the paper by a concluding section.

II. Research Design and Methodology

The objective of the proposed multi-agent modeling is to support the different negotiations between a large number of parts that have many interactions. The proposed modeling applied for the decision support problem, as a case study to cope with complex multi-criteria decision-making situations, is composed of many decision-making elements and tools, the tasks of which can be summarized as explained in the following process:

Process I: During this process a user interface agent specifies the most influential criteria required to evaluate the proposed alternatives. It begins by a detailed description of the problem and generates ideas about the needed criteria to be implemented when making the decision. It is ended when a consensus is reached for the selected criteria.

Process II: After a consensus is reached for the selected criteria, a FAHP (Fuzzy Analytic Hierarchy Process) agent proceeds to decompose the decision-making problem into its constituent parts, construct hierarchies of the influential criteria, construct the fuzzy pairwise comparison matrices, and finally, calculate the final normalized weight of each criterion.

Process III: At this stage, the objective is to evaluate and rank a set of actions (alternatives) considered in the process through the use of OLAP-MCDA agent that combines the analytical capabilities of OLAP systems with the weighted sum, as a multi-criteria decision method, which will exploit the relative importance/weights of the evaluation criteria obtained via the FAHP agent as inputs to evaluate and select the suitable alternatives.

A. The Proposed MAS Architecture

As noticed by several researchers, most problems involve or require multiple agents in order to represent the decentralized nature of the problem, the multiple perspectives, or the competing interests. In fact, each agent needs to create interactions with other agents, either to reach their individual goals or to handle the dependencies that ensue from being situated in a common environment [24]. In this context, our proposed MAS is established to manage and implement the different interactions and negotiations that can be realized within this system. As shown in Fig. 2, four types of agents, namely, the FAHP agent, the coordinator agent, the user interface agent and the OLAP-MCDA agent are involved. The respective tasks and functions of these agents are as follows:

- User Interface Agent (UIA)
  - Represents the decision makers and consults the database to select the evaluation criteria.
- FAHP Agent (FA)
  - Decomposes the decision-making problem into its constituent parts.
  - Constructs hierarchies of the influential criteria.
  - Calculates the importance weights of each criterion.
- Coordinator Agent (CA):
  - Controls the different interactions between agents involving the negotiation model.
  - Configures negotiation strategies.
- OLAP-MCDA Agent (OMA)
  - Receives the weights of criteria as inputs.
  - Combines the analytical capabilities of OLAP systems with the weighted sum as a multi-criteria analysis method.
  - Calculates the weighting within the OLAP-MCDA cube (Fig. 1).
  - Evaluates and ranks alternatives according to the selected criteria and "Time dimension".

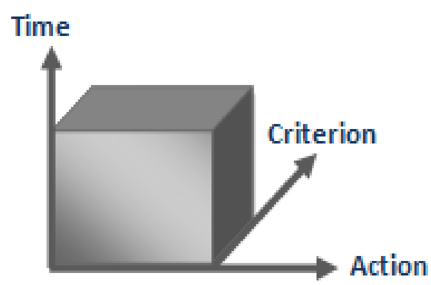


Fig. 1 Abstract representation of the OLAP-MCDA cube

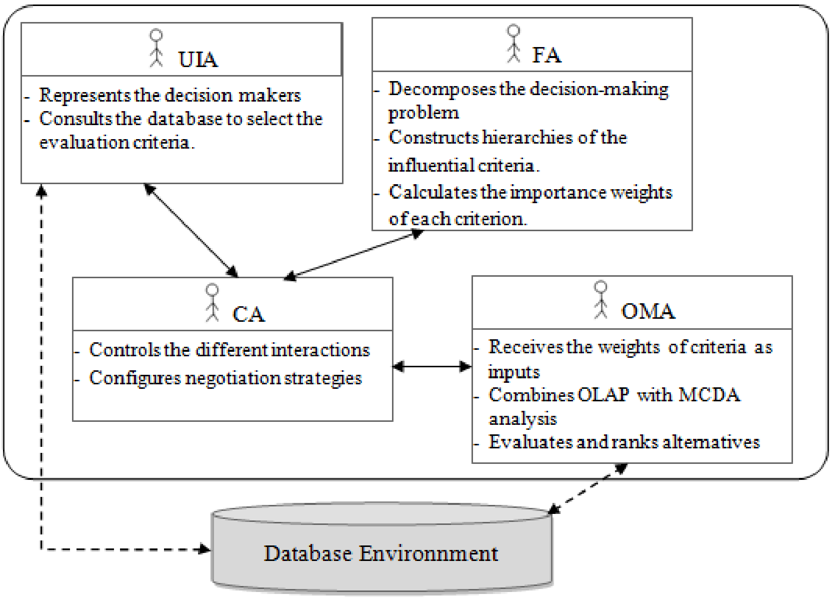


Fig. 2 The proposed MAS architecture for OLAP-MCDA integration process

B. The Proposed Procedure of the Negotiation Model

The used negotiation model is composed of three phases (Fig. 3): identification of criteria, assignment of weights, bargaining and ranking. The functions of the three phases are explained as:

- **Identification of criteria**: the function of this phase includes negotiation between user (decision makers) agents, consulting the data warehouse containing the objective (quantitative) and subjective (qualitative) criteria respecting the aspect of heterogeneities in the selection of criteria, and proposing a set of evaluation criteria when a consensus is reached by decision maker agents.
- **Assigning weight**: the major functions to consider in this phase include receiving the selected criteria, constructing the comparison matrix, converting the appreciations assigned to each criterion to precise value, and finally determining the weight of importance for each criterion following the algorithmic steps of FAHP methods (Buckley's method [25]).
- **Bargaining and ranking**: The function of this phase is to support the multiple bilateral bargaining between the UIA, CA and FA. After receiving the bargaining results, the ranking of alternatives is conducted on the basis of the calculated weight using OMA agent.

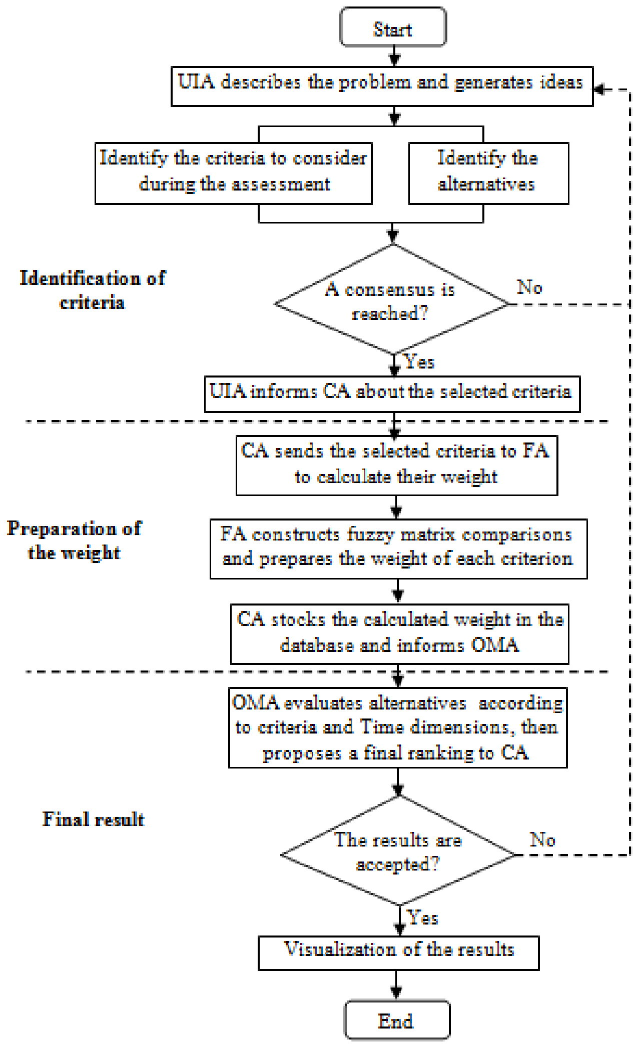


Fig. 3 Procedure of the negotiation model for OLAP-MCDA integration process

C. The Proposed Negotiation Protocol

The negotiation protocol which manages the interaction of agents involved in the negotiation model for integrating the multi-criteria analysis in the OLAP system to deal with the decision support problems, is a hybrid protocol allowing to assign importance weights to the selected criteria, then evaluate and rank the alternatives on the basis of the OLAP - MCDA integration process. The UIA agent selects the evaluation criteria and demands to assign their weights. This request is sent by the CA to the FA to calculate the importance weight based on the algorithm of FAHP extent analysis method and then save them in the data warehouse. After calculating the weight, the UIA asks to evaluate and classify the alternatives via messages expressed in a MDX (Multidimensional Expressions) query on the basis of the previous calculated weights. These queries are sent back by the CA to the OMA for being processed based on the technical and analytical flexibility of OLAP system and multi-criteria analysis. The final results of the alternatives evaluation can be viewed or restituted using the capabilities of the OLAP system included in the OMA agent.

The different interactions of agents according to the proposed negotiation protocol are shown in Fig. 4.

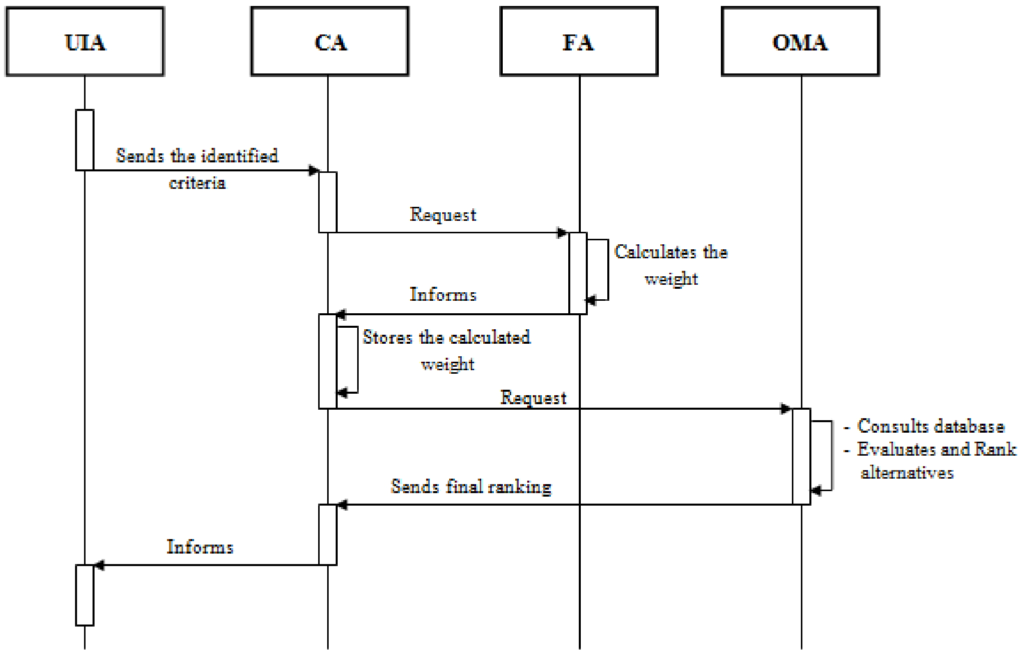


Fig. 4 Protocol of the negotiation model for OLAP-MCDA integration process

III. Methods

A. Algorithmic Process of the FA Functioning

In this paper we prefer to utilize the algorithmic process of Buckley's method [25] to evaluate the importance weight of each selected criterion. The theoretical fundamentals of the Buckley's method were defined as follows:

Step 1: The problem must be decomposed into a hierarchy of interrelated elements (factors and sub-factors). At the top of the hierarchy we find the goal, the elements contributing to achieve it are presented in the lower levels.

Step 2: The fuzzy comparison matrix $\tilde{D}$ is built by conducting pairwise comparisons of the elements of each hierarchical level with respect to an element of the upper hierarchical one. Triangular fuzzy numbers (TFNs) must be established (Table I) by integrating fuzzy opinions on the relative importance of paired elements. The reason for using TFNs to capture the vagueness of the linguistic assessments is that TFN is intuitively easy to use [26], [27].

$$\tilde{D} = \left[\tilde{x}_{ij}\right] = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \tilde{x}_{13} & \dots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \tilde{x}_{23} & \dots & \tilde{x}_{2n} \\ \tilde{x}_{31} & \tilde{x}_{32} & \tilde{x}_{33} & \dots & \tilde{x}_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \tilde{x}_{n3} & \dots & \tilde{x}_{nn} \end{bmatrix}, \text{i, j} = 1, 2 \dots, \text{n} \quad (1)$$

TABLE I
FUZZY COMPARISON MEASURES [28]

Linguistic terms	Triangular fuzzy numbers
Very Good (VG)	(7, 9, 9)
Good (Gd)	(5, 7, 9)
Preferable (P)	(3, 5, 7)
Weak advantage (WA)	(1, 3, 5)
Equal (EQ)	(1, 1, 1)
Less WA	(1/5, 1/3, 1)
Less P	(1/7, 1/5, 1/3)
Less G	(1/9, 1/7, 1/5)
Less VG	(1/9, 1/9, 1/7)

Step 3: For the consistency verification of fuzzy matrix $\tilde{D}$ we assume that $D=\left[x_{ij}\right]$ is a positive reciprocal matrix and its corresponding fuzzy positive reciprocal matrix is $\tilde{D}=\left[\tilde{x}_{ij}\right]$. Therefore, $D=\left[x_{ij}\right]$ is consistent, as well as $\tilde{D}=\left[\tilde{x}_{ij}\right]$.

Step 4: The fuzzy weight ($\tilde{W}_i$) of the fuzzy positive reciprocal matrix is calculated as explained below:

$$\tilde{Z}_i=\left[\prod_{j=1}^{n}\tilde{x}_{ij}\right]^{1/n},\ \text{i, j} = 1,2\ldots\text{n} \tag{2}$$

$$\tilde{W}_i=\tilde{Z}_i\otimes\left(\sum_{i=1}^{n}\tilde{Z}_i\right)^{-1} \tag{3}$$

$\tilde{Z}_i$: Geometric average of triangle fuzzy numbers.

Step 5: During this step, we conduct a defuzzification process using the gravity method as:

$$W_i=\frac{W_{a_1i}\oplus W_{mi}\oplus W_{a_2i}}{3} \tag{4}$$

W_{a_1i} : The value of the minimum fuzzy weight (left value). W_{mi} : The value of the grade of membership of the fuzzy weight. W_{a_2i} : The value of the maximum fuzzy weight (right value). W_i : The conversion of the fuzzy weight of the TFNs into a single value.

Step 6: The final normalized weight (NW) is then obtained as:

$$NW_i=\frac{W_i}{\sum_{i=1}^{n}W_i} \tag{5}$$

B. Evaluation Procedure for OMA Agent

At this stage, the main objective is to evaluate and rank the considered alternatives by combining the analytical capabilities of OLAP systems with the weighted sum method due to its simplicity to be easily integrated within the XML file containing the OLAP cube. Hence, the aggregation of the criteria dimension values will be achieved by introducing different weighting in the evaluation process using (6):

$$u(a_i)=\sum_{j=1}^{k} v_j.r_{ij} \tag{6}$$

where: $u(a_i)$ = utility evaluated of i^{th} alternative; v_j = weight of j^{th} criterion; r_{ij} = utility evaluated of i^{th} alternative for j^{th} criterion.

The major steps considered by OMA agent are:

- Establish the table of performance for the alternatives evaluation, taking into consideration the selected criteria and time dimension;
- Present the impact of integrating the weighted sum on the importance of each criterion during the evaluation;
- Evaluate and rank alternatives using the flexible capabilities of the OLAP analysis.

The described organizational structure bringing multidimensional analysis and performing typical OLAP navigations like drill down, roll up, slice, dice, and pivot is implemented through an open source OLAP server called Mondrian server [29]. For an easy access to data, a user interface called JPivot based on JSP (JavaServer Pages) custom tag library is used. This interface will enable us use MDX queries to screen very fast for a particular subset of data from the XML file containing our OLAP-MCDA cube. During the calculation steps, a measure called 'evaluation' is created with two calculated members: 'weighted sum' and 'multi-criteria aggregation' in order to strengthen the performances of OLAP analysis server.

IV. Results and Discussion

As an illustration of a decision-making problem, the selection of industrial locations to install a new industrial corporation in the region of Casablanca, Morocco, is performed using our multi-agent modeling. This study considers four zones (Zone1, Zone2, Zone3 and Zone4) and controls their evolution over a period of time starting from 2000 to 2014 as mentioned in Table VI.

In the proposed negotiation model, the negotiation issues are divided into three main criteria: Environmental, Economic and Social, and six sub criteria (limited to the most influencing criteria) as:

- Environmental criteria (C1): [Proximity of green areas (C11), Land (C12)].
- Economic criteria (C2): [Free trade zones (C21), Competitive advantages (C22)].
- Social criteria (C3): [Proximity to customers (C31), Manpower availability (C32)].

A simulation is performed to demonstrate the function and effectiveness of the multi-agent modeling for strategic industrial location selection.

A. Experiment 1: Calculating Weight through FAHP Agent

We present in the following an example of weight calculation for main criteria using Buckley's analysis method. The criteria rating is performed using Table I for triangular fuzzy numbers. The fuzzy weight is then obtained on the basis of the geometric average of TFNs using (2), (3), and the final normalized weight is provided using (4), (5) as shown in Table III.

TABLE II
COMPARISON MATRIX FOR THE MAIN CRITERIA

Objective	Environment	Economic	Social
Environment	(1, 1, 1)	(1, 3, 5)	(3, 5, 7)
Economic	(1/5, 1/3, 1)	(1, 1, 1)	(1, 3, 5)
Social	(1/7, 1/5, 1/3)	(1/5, 1/3, 1)	(1, 1, 1)

TABLE III
THE GEOMETRIC AVERAGE ($\tilde{Z}_i$), FUZZY WEIGHT ($\tilde{W}_i$) AND FINAL NORMALIZED WEIGHT (NW_i)

Main Criteria	Geometric average ($\tilde{Z}_i$)	Fuzzy weight ($\tilde{W}_i$)	Defuzification (W_i)	Final normalized weight (NW_i)
Environment	(1.442, 2.466, 3,271)	(0.618, 0.637, 0,576)	0,611	0,611
Economic	(0.585, 1.000, 1,710)	(0.251, 0.258, 0,301)	0,270	0,270
Social	(0.306, 0.405, 0,693)	(0.131, 0.105, 0,122)	0,119	0,119

Following the same systematic methodology (Tables II, III) for the other evaluations, we get the priority weights correspondingly for each criterion and sub criterion as explained in Table IV.

TABLE IV
FINAL CRITERIA WEIGHT

Criteria	Fuzzy weight	Final normalized weight
C1	(0.618, 0.637, 0,576)	-
C11	(0.188, 0.167, 0.188)	0.111
C12	(0.813, 0.833, 0.813)	0.501
C2	(0.251, 0.258, 0,301)	-
C21	(0.667, 0.750, 0.667)	0.188
C22	(0.333, 0.250, 0.333)	0.082
C3	(0.131, 0.105, 0,122)	-
C31	(0.134, 0.125, 0.134)	0.016
C32	(0.867, 0.875, 0.867)	0.103

B. *Experiment 2: Final Analysis Using OMA Agent*

As already mentioned, MDX queries will be used to represent the information of the OLAP-MCDA cube as shown in Fig. 5 using OMA agent to perform the necessary calculations, and UIA agent to represent the results.

During this experiment, the rating of each alternative as explained in Table VI is performed using membership functions depicted in Table V.

TABLE V
TRANSFORMATION FOR FUZZY MEMBERSHIP FUNCTIONS

Linguistic Terms	Membership function
Very High (VH)	(0.75, 0.90, 1.00) 0,883
High (H)	(0.55, 0.70, 0.85) 0,700
Medium (M)	(0.35, 0.50, 0.65) 0,500
Low (L)	(0.15, 0.30, 0.45) 0,300
Very Low (VL)	(0.00, 0.10, 0.25) 0,117

TABLE VI
DECISION MAKERS' JUDGMENTS OVER A DEFINED PERIOD OF TIME

Time	Criteria	Zone1	Zone2	Zone3	Zone4
2000	C11	(0.15, 0.30, 0.45)	(0.35, 0.50, 0.65)	(0.15, 0.30, 0.45)	(0.00, 0.10, 0.25)
	C12	(0.00, 0.10, 0.25)	(0.15, 0.30, 0.45)	(0.35, 0.50, 0.65)	(0.15, 0.30, 0.45)
	C21	(0.15, 0.30, 0.45)	(0.15, 0.30, 0.45)	(0.35, 0.50, 0.65)	(0.00, 0.10, 0.25)
	C22	(0.00, 0.10, 0.25)	(0.35, 0.50, 0.65)	(0.15, 0.30, 0.45)	(0.15, 0.30, 0.45)
	C31	(0.35, 0.50, 0.65)	(0.15, 0.30, 0.45)	(0.00, 0.10, 0.25)	(0.15, 0.30, 0.45)
	C32	(0.15, 0.30, 0.45)	(0.15, 0.30, 0.45)	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)
2007	C11	(0.00, 0.10, 0.25)	(0.55, 0.70, 0.85)	(0.15, 0.30, 0.45)	(0.55, 0.70, 0.85)
	C12	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)	(0.55, 0.70, 0.85)	(0.15, 0.30, 0.45)
	C21	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)	(0.15, 0.30, 0.45)
	C22	(0.15, 0.30, 0.45)	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)	(0.15, 0.30, 0.45)
	C31	(0.35, 0.50, 0.65)	(0.15, 0.30, 0.45)	(0.15, 0.30, 0.45)	(0.35, 0.50, 0.65)
	C32	(0.35, 0.50, 0.65)	(0.15, 0.30, 0.45)	(0.55, 0.70, 0.85)	(0.55, 0.70, 0.85)
2014	C11	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)
	C12	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)
	C21	(0.35, 0.50, 0.65)	(0.75, 0.90, 1.00)	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)
	C22	(0.15, 0.30, 0.45)	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)
	C31	(0.55, 0.70, 0.85)	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)	(0.75, 0.90, 1.00)
	C32	(0.35, 0.50, 0.65)	(0.35, 0.50, 0.65)	(0.75, 0.90, 1.00)	(0.55, 0.70, 0.85)

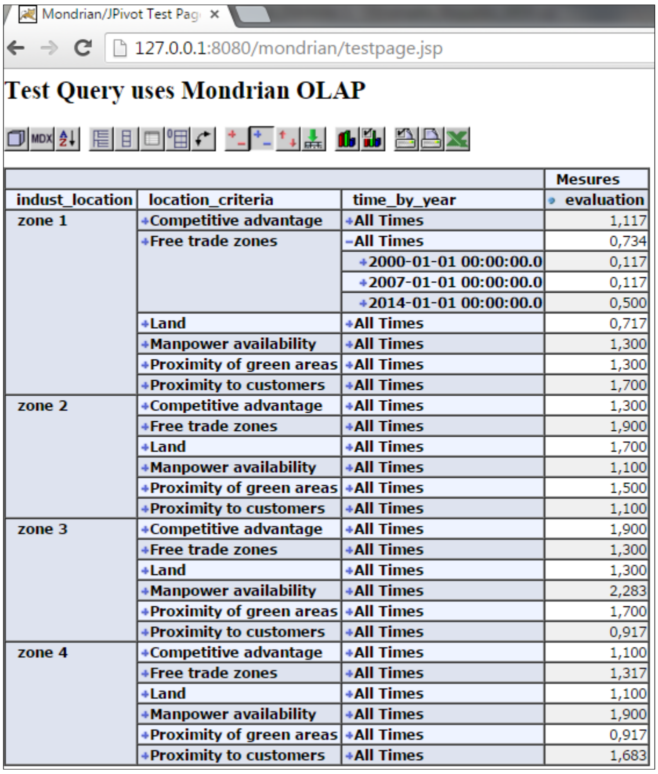
Q1:

```
SELECT {[Measures]. [Evaluation]} ON COLUMNS,
Crossjoin(Crossjoin(
{[Indust_location].[All
Locations].Children},{[Location_criteria].[All
Criteria].Children}),
{[Time_by_year].[All Times]})
ON ROWS
FROM [Evaluation]
```

By exploiting the analytical mechanisms of OLAP server to move up in the hierarchy of the cube, the representation of the results is performed after the final ranking of multi-criteria aggregation for all locations.

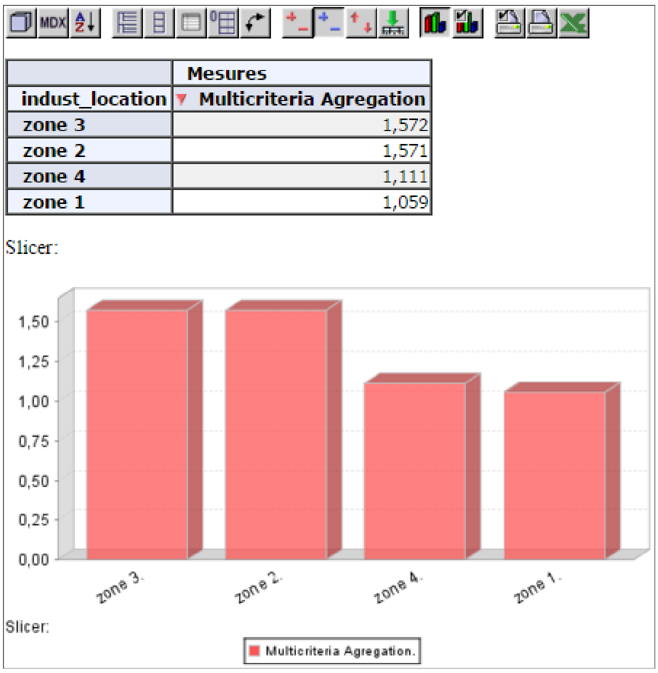
The following MDX query represents the final result as graphically shown in Fig. 6.

Using the graphical representation of the OLAP Mondrian server, the final ranking of potential industrial location is provided as shown in Fig. 6. In fact, OLAP graphically displays the relative score of each alternative on the basis of the contribution of each selected criterion. The most suitable industrial location is the one with the highest score as illustrated in Fig. 6, which reveals that zone 3 is the preferred location with a score of 1.572, followed by zone 2 (1.571), zone 4 (1.111) and finally zone 1 (1.059).



			Mesures
indust_location	location_criteria	time_by_year	evaluation
zone 1	Competitive advantage	All Times	1,117
	Free trade zones	All Times	0,734
		2000-01-01 00:00:00.0	0,117
		2007-01-01 00:00:00.0	0,117
		2014-01-01 00:00:00.0	0,500
	Land	All Times	0,717
	Manpower availability	All Times	1,300
	Proximity of green areas	All Times	1,300
	Proximity to customers	All Times	1,700
zone 2	Competitive advantage	All Times	1,300
	Free trade zones	All Times	1,900
	Land	All Times	1,700
	Manpower availability	All Times	1,100
	Proximity of green areas	All Times	1,500
	Proximity to customers	All Times	1,100
zone 3	Competitive advantage	All Times	1,900
	Free trade zones	All Times	1,300
	Land	All Times	1,300
	Manpower availability	All Times	2,283
	Proximity of green areas	All Times	1,700
	Proximity to customers	All Times	0,917
zone 4	Competitive advantage	All Times	1,100
	Free trade zones	All Times	1,317
	Land	All Times	1,100
	Manpower availability	All Times	1,900
	Proximity of green areas	All Times	0,917
	Proximity to customers	All Times	1,683

Fig. 5 Representation of OLAP-MCDA Hybrid cube



	Mesures
indust_location	Multicriteria Agregation
zone 3	1,572
zone 2	1,571
zone 4	1,111
zone 1	1,059

Fig. 6 Final representation of the results

V. Conclusions

In this article, we have described how the integration of multi-criteria decision analysis (MCDA) with OLAP systems can generate a unified analysis process dealing with complex decision making situations. We have tried to demonstrate the potential of multi-agent system to significantly improve our ability to design and model complex situations by decomposing the problem, creating tasks and allocating them to specific agents. In this context, the multi-agent based modeling presented in this paper for decision support systems, using multi-criteria decision analysis with OLAP system, is composed of a MAS architecture, procedure and protocol of the negotiation model to describe and control individual and collective tasks that each agent must execute. For this reason, an illustrative example is conducted to demonstrate the functioning and effectiveness of our multi-agent modeling in a complex decision-making situation.

Although this paper has focused predominantly on the intake of combining MCDA with OLAP system, with the advantage of using multi-agents system to model and simplify this integration process for complex decision-making situations, the proposed multi-agents modeling should not be viewed merely as a proposed solution technology. Rather, it should be seen in its broader context as a general-purpose model presented to understand and support decision makers when faced with complex decision-making situations. In this regard, as a perspective, we will develop a web framework based on our MAS modeling to allow the consideration of multiple users (decision-makers) in the same decision making process and at the same negotiating context, which will maximize the degree of certainty and reliability in the final decision making results.

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References

[1] Wooldridgey, M., & Ciancarini, P. (2001, January). Agent-oriented software engineering: The state of the art. In Agent-oriented software engineering (pp. 1-28). Springer Berlin Heidelberg.

[2] Nourani, C. F. (2002). Agent-Based Software Engineering and Agent Mediations. Hybrid Information Systems, 469–484. doi:10.1007/978-3-7908-1782-9_34

[3] O'Hare, G. M., & Jennings, N. (1996). Foundations of distributed artificial intelligence (Vol. 9). John Wiley & Sons.

[4] S. D. J. McArthur, S. M. Strachan, and G. Jahn, "The design of a multi-agent transformer condition monitoring system," IEEE Transactions on Power Systems, vol. 19, no. 4, pp. 1845–1852, 2004.

[5] D. P. Buse and Q. H. Wu, "Mobile agents for remote control of distributed systems," IEEE Transactions on Industrial Electronics, vol. 51, no. 6, pp. 1142–1149, 2004.

[6] E. M. Davidson, S. D. J. McArthur, J. R. McDonald, T. Cumming, and I. Watt, "Applying multi-agent system technology in practice: automated management and analysis of SCADA and digital fault recorder data," IEEE Transactions on Power Systems, vol. 21, no. 2, pp. 559–567, 2006.

[7] K. Fregene, D. C. Kennedy, and D. W. L. Wang, "Toward a systems- and control-oriented agent framework," IEEE Transactions on Systems, Man, and Cybernetics, Part B, vol. 35, no. 5, pp. 999–1012, 2005.

[8] García Ansola, P., de las Morenas, J., García, A., & Otamendi, J. (2012). Distributed decision support system for airport ground handling management using WSN and MAS. Engineering Applications of Artificial Intelligence, 25(3), 544–553.

[9] Ibri, S., Nourelfath, M., & Drias, H. (2012). A multi-agent approach for integrated emergency vehicle dispatching and covering problem. Engineering Applications of Artificial Intelligence, 25(3), 554–565.

[10] Dou, C., Wang, W., Hao, D.-W., & Li, X. (2015). MAS-based solution to energy management strategy of distributed generation system. International Journal of Electrical Power & Energy Systems, 69, 354–366.

[11] Narayanaswami, S., & Rangaraj, N. (2015). A MAS architecture for dynamic, realtime rescheduling and learning applied to railway transportation. Expert Systems with Applications, 42(5), 2638–2656.

[12] Kaya, M., & Alhajj, R. (2014). Development of multidimensional academic information networks with a novel data cube based modeling method. Information Sciences, 265, 211–224.

[13] Lotfy, H. M. S., Khamis, S. M. S., & Aboghazalah, M. M. (2015). Multi-Agents and Learning: Implications for WebUsage Mining. Journal of Advanced Research. doi:10.1016/j.jare.2015.06.005

[14] Cao, M., Luo, X., Luo, X. (Robert), & Dai, X. (2015). Automated negotiation for e-commerce decision making: A goal deliberated agent architecture for multi-strategy selection. Decision Support Systems, 73, 1–14.

[15] Shen, Y., Colloc, J., Jacquet-Andrieu, A., & Lei, K. (2015). Emerging medical informatics with case-based reasoning for aiding clinical decision in multi-agent system. Journal of Biomedical Informatics, 56, 307–317

[16] Sun, B., & Ma, W. (2015). Rough approximation of a preference relation by multi-decision dominance for a multi-agent conflict analysis problem. Information Sciences, 315, 39–53

[17] Neville, B., Fasli, M., & Pitt, J. (2015). Utilising social recommendation for decision-making in distributed multi-agent systems. Expert Systems with Applications, 42(6), 2884–2906

[18] Santos, G., Pinto, T., Morais, H., Sousa, T. M., Pereira, I. F., Fernandes, R., … Vale, Z. (2015). Multi-agent simulation of competitive electricity markets: Autonomous systems cooperation for European market modeling. Energy Conversion and Management, 99, 387–399

[19] Kaya M, Alhajj R (2005) Fuzzy OLAP Association Rules Mining-Based Modular Reinforcement Learning Approach for Multiagent Systems. IEEE Transactions on Systems, Man, and Cybernetics—Part B: Cybernetics 35(2):326–338

[20] Rupnik R, Kukar M (2007) Data Mining Based Decision Support System to Support Association Rules. Elektrotehniski vestnik 74(4):195–200

[21] Lavbi D, Rupnik R (2009) Multi-Agent System for Decision Support in Enterprises. Journal of Information and Organizational Sciences 33(2):269–284

[22] Srinivasan S, Singh J, Kumar V (2011) Multi-agent based decision Support System using Data Mining and Case Based Reasoning. International Journal of Computer Science 8(4):340–349

[23] Markic I, Stula M, Maras J (2014) Intelligent Multi Agent Systems for decision support in insurance industry. 37th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO'2014) 1118–1123

[24] Jennings N. R., and Wooldridge M. (2001). Agent-Oriented Software Engineering, Handbook of agent technology, ed. J. Bradshaw, AAAI/MIT Press.

[25] Buckley J.J (1985) Fuzzy hierarchical analysis. Fuzzy Sets and Systems, 17 (3): 233–247

[26] Tsao C.-T, Chu C.-T (2001) Personnel selection using an improved fuzzy MCDM algorithm. Journal of Information and Optimization Sciences 22(3): 521–536

[27] Kannan G, Pokharel S, Sasi Kumar P (2009) A hybrid approach using ISM and fuzzy TOPSIS for the selection of reverse logistics provider. Resources, Conservation and Recycling 54(1): 28–36

[28] Gumus, A.T., 2009. Evaluation of hazardous waste transportation firms by using a two step fuzzy-AHP and TOPSIS methodology. Expert Systems with Applications. 36,4067-4074.

[29] Pentaho community, Mondrian: Http://community.pentaho.com/projects/mondrian/. Accessed 3 August 2015