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Multi-criteria Decisional Approach of the OLAP Analysis by Fuzzy Logic: Green Logistics as a Case Study

Omar Boutkhoum[1] · Mohamed Hanine[1] · Abdessadek Tikniouine[1] · Tarik Agouti[1]

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Abstract This study aims to propose a decision-making approach combining multi-criteria analysis and fuzzy logic within the online analytical processing data cube model (OLAP). Indeed, most decision-making systems are based on models of operational research. These models are often composed of quantitative data and postulate the existence of a single objective function (criterion) representing the preferences of decision-makers. However, in reality, we are faced with a more complex situation where several criteria (quantitative and/or qualitative) should be taken into account. It is therefore natural to consider different types of data (more criteria) in the design of OLAP cubes and decision-making systems. Multi-criteria decision analysis (MCDA) combined with fuzzy sets theory offers an efficient approach to solve complex decision problems. So we believe it is useful and necessary to envisage, for OLAP cubes, an optimized data model taking into account several criteria, on which we can apply new methods of MCDA. We end our contribution by applying the decision support process of this paper to propose a scheme of green logistics for large industrial zones in the city of Casablanca, Morocco.

Keywords Multidimensional analysis · OLAP analysis · Multi-criteria decision analysis · Analytic hierarchy process (AHP) · Fuzzy logic · Decision-making system

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✉ Omar Boutkhoum
o.boutkhoum@uca.ma

Mohamed Hanine
h.hanine@uca.ma

Abdessadek Tikniouine
tikniouine@uca.ma

Tarik Agouti
t.agouti@uca.ma

[1] Laboratory of Information Systems Engineering, Department of Computer Science, Faculty of the Sciences Semlalia, Cadi Ayyad University, Marrakech, Morocco

1 Introduction

Recently, the business intelligence (BI) suites and particularly OLAP systems are considered among the most prominent and powerful technologies in DSS environment. In fact, OLAP systems are at the heart of many business analytics applications and appear as complete systems that provide helpful and necessary services for a rational and efficient treatment of intelligence data. In this kind of models, the data are well organized multidimensionally so that the decision-makers could analyze them interactively and iteratively at a detailed and/or aggregated level. The OLAP functionalities based on an approach of multidimensional databases [1] are characterized, as in [2], by its ability to support effective and flexible exploration of multidimensional cubes in data warehouses, which provide an efficient analysis from multiple dimensions or perspectives for a large amount of data residing in a data warehouse. The multidimensional database as a data model, on which OLAP relies heavily, has the following three advantages:

– Performance: multidimensional database increases performance. Indeed, OLAP operations (e.g., drill down, roll up, slice, dice, and pivot) enable intuitively the analyst to make a focused research through the database and screen very fast for a particular subset of the data.

– Ease of maintenance: the maintenance of multidimensional databases is very easy, because data are stored in the same way as they are viewed.
– Presentation: the data presentation and navigation are enhanced by multidimensional databases using intuitive spreadsheet-like views.

In a multidimensional data analysis system, the data are organized around fact tables and one or more numerical indicators (called measures) grouped by a given set of analysis axes (called dimensions). Through the exploitation of multidimensional views of the data warehouse, OLAP server, which is relying on classical data model known as the data cube [3], enables users to perform many statistical operations such as forecasting and ranking. In fact, the data returned by an OLAP query take the form of a multidimensional cube and can be illustrated either textually or graphically, which helps users to view organizational data at a variety of granularity levels, i.e., detailed or summarized through the use of drill-down and roll-up operations, respectively, from different perspectives.

Several studies have been conducted around the topic of OLAP technology reflecting its degree of importance and its effectiveness to be implemented in multiple business intelligence areas. For example, Gkesoulis et al. [4] try to demonstrate the possibility of producing query results that are properly visualized, textually exploitable, and vocally enriched, which gives insights into the original results of an OLAP query. In order to overcome information flooding that may occur during an OLAP session, Golfarelli et al. [5] propose a novel OLAP operation with the aim of balancing data precision with data size in cube visualization using pivot tables. A new framework for cyclic association rules mining from parallel hierarchies is presented by Ben Ahmed et al. [6] through the integration of data warehouse, OLAP, and data mining where multiple hierarchies are associated with a given dimension with respect to several analytical purposes.

Furthermore, OLAP system has been widely combined with many other decision technologies especially big data. As example, Cuzzocrea et al. [7] investigate the parallel building of OLAP data cubes, adapted to novel big data environments. Song et al. [8] try to implement the Hadoop-based multidimensional OLAP system for big data environment by adopting the specified multidimensional model to map the dimensions with measures among HaoLap (Hadoop-based OLAP). The contribution of Kang et al. [9] proposes an efficient indexing for OLAP query processing with MapReduce in order to insert the data and index into separate blocks and force them to be colocated in the same node. Combining OLAP with cloud computing is also introduced by Dehne et al. [10] for a scalable cloud architecture-based real-time OLAP system which relies on a new distributed index structure for OLAP. In addition, Al-Aqrabi et al. [11] investigate the possibility of implementing BI and particularly OLAP systems on the cloud which is reflected in their simulation results explaining that OLAP application demands can be efficiently processed on cloud computing.

Many other researchers explain the ability of OLAP system to control and optimize computing time via its analytic flexibility, which minimizes the access time to information and ensures easy exploitation for huge data of data warehouse. Therefore, we can say that OLAP system is a relatively well-mastered technology when it comes to simple data, which explains its ability to be easily integrated with other technologies such as big data and cloud computing. However, in multi-criteria decision-making situations, we could not find any simple or hybrid OLAP model to deal with the problem of selection. In addition, OLAP has some limitations due to the complexity coming from the presence of more than one criterion during the data analysis and the lack of structuring complex situations requiring a huge number of data (both qualitative and quantitative, subject to analysis), which will certainly lead to bad consequences (as also mentioned in the literature by Lee et al. [17]) such as failure in achieving decision quality improvement, low decision-makers' satisfaction, and occasionally long analysis cycle times.

With the aim of tackling these problems, we naturally introduce a new analytical approach through the use of multi-criteria decision analysis (MCDA) and fuzzy set theory to enhance the analytical capabilities within OLAP systems. Indeed, the MCDA aims to provide tools for the decision-makers allowing them to progress in solving a decision problem where several viewpoints, often conflicting, must be taken into account. In this paper, we study the impact of multi-criteria analysis on the OLAP systems and investigate the adaptation of OLAP to deal with complex situations, especially when combined with multi-criteria analysis and fuzzy set theory, which will allow us to take into account the multi-criteria and qualitative aspects of the data and then minimize the degree of imprecision and uncertainty during the analysis process. Effectively, we use OLAP normally to analyze structured data, but with the rapid spread of the decision information, it must adapt to manage this heterogeneous BI information helping in the management, treatment, and resolution of complex decision-making problems. Following these considerations, the main objective of this work is to propose a methodological approach to create a data cube hybrid model (OLAP/MCDA) for the OLAP systems. We involve both multi-criteria decision analysis and fuzzy logic in the OLAP analysis process.

The remainder of this paper is organized as follows: In Sect. 2, related work is presented. The contribution of both multi-criteria analysis and fuzzy logic is proposed in Sect. 3. Section 4 discusses our integrated approach combining multi-criteria analysis and fuzzy logic within the OLAP data cube model. In Sect. 5, we focus our attention on an empirical study to illustrate the effectiveness and performance of our approach, where a sensitivity analysis is also given. Lastly, this paper is ended by a concluding section.

2 Related Work

The research topics that are intimately related to the present study are: multi-criteria analysis, fuzzy set theory, and OLAP analysis. The researchers have used different approaches based on these orientations in order to propose and select the most appropriate solutions dealing with complex decision problems. In this context, the application of fuzzy sets to databases and OLAP cubes has been decisive in many treatments to obtain several solutions. For example, Galindo et al. [12] propose a design and implementation of fuzzy databases modeling focusing on some new semantic aspects. In addition, a new fuzzy SQL for fuzzy databases to handle and process fuzzy information in fuzzy and/or crisp databases is presented in [13], by using new definitions including five new fuzzy attributes and fuzzy constant types, four new fuzzy comparators, and new characteristics in the fulfillment thresholds and dynamic change of functions in logic operations. González et al. [14] provide fuzzy OLAP operators in a formal way in order to avoid imprecision and uncertainty and support qualitative analysis. The research presented by Kaya and Alhajj [15] try to perform automated decision processes by developing three different academic networks with a novel data cube based modeling method, which leads them to use the OLAP technology in order to appropriately analyze the data cube.

Other works discuss the possible combination opportunities with OLAP systems, as the contribution of Loudcher et al. [16], exploring the interest of combining OLAP analysis and information networks in providing a new way of analyzing bibliographic data. The information networks should be handled by OLAP which will be useful for monitoring and analyzing the structure and the content of the bibliographic networks. A hybrid OLAP association rule mining-based quality management system is presented by Lee et al. [17] in order to extract defect patterns in the garment industry and allow data mining to be applied on a multidimensional basis. In the same context, Meyer et al. [18] present their approach integrating data mining results into multidimensional data warehouse structures, which enables the end-user to easily access data mining results, using simple OLAP queries, and also combines these results with the original information stored in the data warehouse.

Numerous studies have been conducted over the years to explore the analytical power of the OLAP system and its ability to be easily combined with other technologies for the same purpose of increasing the analytical capabilities within the OLAP system. However, to the best of our knowledge, we could not find any other integration approach in the literature review combining multi-criteria analysis concepts and fuzzy logic within the OLAP data cube model.

Next, we present some of the existing works in the literature related to the selection problem in the first process of our methodology approach combining AHP as a multi-criteria analysis method with fuzzy sets theory. Indeed, the fuzzy AHP has been widely used for many selection problems. For instance, Somsuk and Laosirihongthong [19] have applied fuzzy AHP to prioritize enabling factors for strategic management of university business incubators using evidence from Thailand. See also [20] integrating fuzzy AHP and fuzzy comprehensive evaluation method as a novel framework for evaluating teaching performance. The authors have used fuzzy AHP to calculate the factor and sub-factor weights, while the fuzzy comprehensive evaluation method is conducted to evaluate teaching performance.

Other works have used a hybrid model integrating fuzzy AHP with other analysis methods, especially TOPSIS, PROMETHEE, and Delphi, such as in [21], trying to identify and prioritize the solutions of knowledge management adoption in supply chain by the use of fuzzy AHP–TOPSIS framework to assign the importance weight to the evaluation criteria and then rank alternatives. In the contribution of Taylana et al. [22], fuzzy AHP and fuzzy TOPSIS methodologies are used to evaluate the construction projects and their overall risks under uncertain and incomplete situations. The same integrated approach based on fuzzy TOPSIS–AHP is conducted by Beikkhakhian et al. [23] to weight suppliers selection criteria using fuzzy AHP and ranking the suppliers by TOPSIS method. In addition, fuzzy AHP combined with fuzzy Kano is also used such in the example Wang and Wang [24] for the optimization of product varieties for smart cameras. The fuzzy AHP is used to extract customers' preferences for core attributes, while fuzzy kano model is applied to elicit customers' perceptions of optional attributes. Many other researches such as [25,26] have used AHP combined with fuzzy set theory in their studies especially for hierarchically structuring the problem and assigning weight to criteria, taking into account human thoughts in making the best decision.

There are other contributions that have used fuzzy PROMETHEE as a multi-criteria decision-making method to address the selection problem as the example of Chen [27] developing an interval type 2 fuzzy PROMETHEE method to address MCDA problems. The author presents a novel likelihood-based preference functions and develops two algorithmic procedures to obtain complete rankings. In addition, Kilic et al. [28] propose a hybrid methodology based on analytical network process (ANP) and PROMETHEE for ERP system selection. Other integrated methodologies have been presented such as the contribution of Wan [29] which proposes an integrated decision-making approach based on fuzzy Delphi, fuzzy extent analysis, and fuzzy TOPSIS to evaluate green operations initiatives and ensure more rational selection decisions. Moreover, Parameshwaran et al. [30] have used a multidisciplinary approach to develop a framework based on fuzzy Delphi method (FDM), fuzzy interpretive structural modeling (FISM), fuzzy ANP (FANP), and fuzzy quality function deployment (FQFD) for a new mechatronics product development. In this context of multidisciplinary approach, we propose in this paper an integrated approach presenting the intake of the multi-criteria decision analysis methods in the OLAP systems. Therefore, the contribution and choice of the MCDA method are briefly described in the following section.

3 Research Methodologies

In this section, we discuss the various steps constructing our proposed methodology, and we start with the contribution of MCDA as follows:

3.1 Contribution and Choice of the MCDA Approach

A problem that requires several criteria can be confused in the absence of a logical and well-structured decision-making process. In this context, the MCDA methodologies are developed to deal with complex situations that involve multiple, usually conflicting decision criteria which include qualitative and/or quantitative aspects in a decision-making process. Many methods of multi-criteria decision analysis have been proposed to enable decision-makers to make the right choice for their decisions. These methods can be grouped into two approaches [31]: methods of the unique approach of synthesis such as TOPSIS, SMART, WEIGHTED SUM, MAUT, MAVT, UTA, AHP, ANP and the outranking methods of synthesis as PROMETHEE, ELECTRE, and ORESTE. Indeed, in this article, we have chosen the AHP method in the first process for hierarchically structuring the problem and attributing a weight of importance to each criterion belonging to this structure. Actually, the criteria weights can be specified by decision-makers indicating their level of knowledge expertise. However, defining these weights directly by decision-makers has some limitations due to the varied importance of the selected criteria, requiring high certainty when allocating these weights. In this context, other multi-criteria decision-making methods such as ANP can be used to measure the relative importance weights by using pairwise comparisons. The main difference between ANP and AHP is that ANP structures a decision problem as a network by taking into consideration the dependence and feedback among the criteria [32], while AHP solves problems when subjectivity exists and where the decision criteria can be organized in a hierarchical way into sub-criteria, which each element in the hierarchy is considered to be independent of all the others. Therefore, integrating the AHP methodology with fuzzy set theory as a first process into our approach is performed taking into consideration the above motivations.

Concerning the evaluation and ranking of actions, as a second process, we choose the method of weighted sum thanks to the simplicity of its mathematical model, which will be easily integrated within the XML file of the OLAP cube. In addition, the optimal solution of a weighted sum is effective. However, this method has some limitations due in particular to the interpretation of the weights that take into account the relative importance of the selected criteria and also the normalization factor of the scales of these criteria. Hence, the weighted sum method needs to have comparable criteria and to incorporate the influence of the prior normalization. For these reasons, fuzzy set theory and AHP method have been used to overcome these limitations by conducting the comparison matrices of all criteria in order to evaluate and identify the weight of importance of each criterion and also to avoid the uncertainty of the decision-makers appreciations when evaluating the criteria.

Before processing the principle of the fuzzy AHP, as a powerful decision-making methodology, we briefly review the rationale for the fuzzy theory as follows:

3.2 Fuzzy Logic

The theory of fuzzy sets was first introduced by Zadeh [33] to deal with the uncertainty due to vagueness or imprecision of human thoughts in making the best decision. In practical selection problems, the fuzzy set theory is very helpful for the decision-makers in using linguistic expressions to express their judgments rather than representing them in the terms of precise numbers. In this context, Zadeh proposes to define linguistic concepts through a functional application that corresponds to any element of the universe its membership degree to the concept underlying.

A fuzzy set A of the universe X is characterized by a membership function μ_A:

If μ_A is the membership function of the fuzzy set A, $\forall x \in X \mu_A \in [0,1]$.

The set A is defined by $A = \{(x, \mu_A(x)) | x \in X\}$.

If $\mu_A(x) = 0, 10$, then x belongs to the fuzzy set A with a membership degree of 10 % which explains low membership (linguistic value ‘low’) with respect to $\mu_A(x) = 0, 90$ which means a very high membership of 90 % (linguistic value ‘very high’).

The fuzzy numbers are used to model imprecise numerical quantities (weak, weak advantage, good, very good, etc.). In fact, they are a special case of fuzzy sets used to evaluate the relative importance of each criterion and to rate the alternatives with respect to various criteria.

For representing fuzzy numbers, the triangular and trapezoidal shapes of membership functions are used in several fields of scientific research. Effectively, triangular fuzzy numbers (TFNs) are frequently used for multi-criteria problems. Hence, we use TFNs in our integrated approach to deal with uncertainty and vagueness of appreciations.

A membership function of a triangular fuzzy number M can be defined by a triplet (a, m, b) as follows:

$$\mu_M(x) = \begin{cases} 0, x \leq a \\ (x-a)/(m-a), a < x \leq m \\ (b-x)/(b-m), m < x \leq b \\ 0, x > b \end{cases} \quad (1)$$

where m is the most probable value of M, and 'a' and 'b,' respectively, the smallest and the largest possible value of M (such that $a \leq m \leq b$).

The fuzzy number M is triangular if m is unique with $\mu_m(m) = 1$ (Fig. 1), and trapezoidal when $m_1 \leq m \leq m_2$ with $\mu_m(m_1) = \mu_m(m_2) = 1$ (Fig. 2). The triangular fuzzy numbers are therefore a special case of trapezoidal fuzzy numbers ($m_1 = m_2$).

The basic operations on fuzzy triangular numbers are as follows:

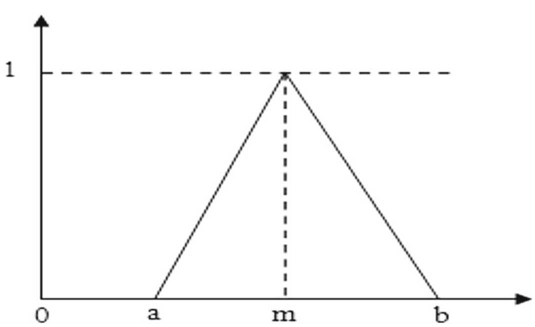


Fig. 1 Triangular representation

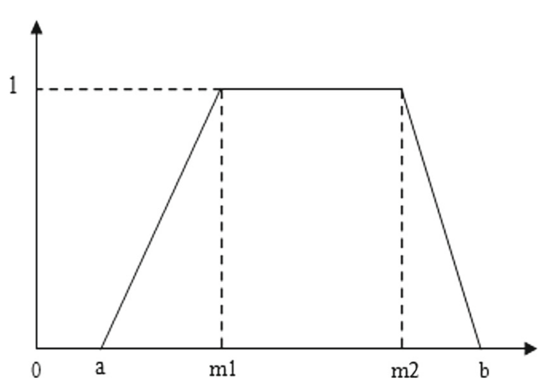


Fig. 2 Trapezoidal representation

For multiplication:

$$(a_1, m_1, b_1) * (a_2, m_2, b_2) = \left(a_1 * a_2, m_1 * m_2, b_1 * b_2\right) \quad (2)$$

Addition:

$$(a_1, m_1, b_1) + (a_2, m_2, b_2) = (a_1 + a_2, m_1 + m_2, b_1 + b_2) \quad (3)$$

Division:

$$(a_1, m_1, b_1) / (a_2, m_2, b_2) = (a_1/b_2, m_1/m_2, b_1/a_2) \quad (4)$$

Reciprocal:

$$(a_1, m_1, b_1)^{-1} = (1/b_1, 1/m_1, 1/a_1)$$
$$\text{For } a_1, a_2 > 0; m_1, m_2 > 0; b_1, b_2 > 0 \quad (5)$$

3.3 Fuzzy AHP Method

Since its introduction by Saaty [34], the analytic hierarchy process (AHP) becomes a flexible and simple systematic methodology used frequently by researchers and practitioners to rank decision alternatives and select the best one when the decision-maker has multiple criteria [35]. The AHP method consists in representing a decision problem by a hierarchical structure, reflecting the interactions between the various elements of this problem, then proceeding to pairwise comparisons of the elements of the hierarchy, and finally identifying priorities for actions.

The AHP method has been applied in several situations thanks to its ability to simplify and solve complex decision problems. However, the pure AHP model has some shortcomings [36]. The use of the discrete scale of AHP is simple and easy, but it does not take into account the uncertainty associated with the mapping of human judgment to a number using natural language. To overcome this limit, several researchers, including those mentioned in the literature review, combine fuzzy sets theory with AHP analysis to represent this type of fuzzy data and improve the uncertainty of decision-maker's judgment.

The steps of fuzzy AHP are explained as follows:

Step 1 Decompose the problem into a hierarchy of interrelated elements. The goal is at the top of the hierarchy, while the elements that contribute to achieve this goal are in the lower levels.

Step 2 Conduct pairwise comparisons of the elements of each hierarchical level with respect to an element of the upper hierarchical level.

Table 1 Example of membership function of linguistic term defined by Gumus [37]

Fuzzy numbers	Linguistic variables	Triangular fuzzy numbers (TFN) scale
9	Very good (VG)	7, 9, 9
7	Good (G)	5, 7, 9
5	Preferable (P)	3, 5, 7
3	Weak advantage (WA)	1, 3, 5
1	Equal (EQ)	1, 1, 1
3^{-1}	Less WA	1/5, 1/3, 1
5^{-1}	Less P	1/7, 1/5, 1/3
7^{-1}	Less G	1/9, 1/7, 1/5
9^{-1}	Less VG	1/9, 1/9, 1/7

$$\begin{bmatrix} 1 & a_{12} & a_{13} & a_{14} & a_{15} & \cdots & a_{1n} \\ a_{21} & 1 & a_{23} & a_{24} & a_{25} & \cdots & a_{2n} \\ a_{31} & a_{32} & 1 & a_{34} & a_{35} & \cdots & a_{3n} \\ a_{41} & a_{42} & a_{43} & 1 & a_{45} & \cdots & a_{4n} \\ a_{51} & a_{52} & a_{53} & a_{54} & 1 & \cdots & a_{5n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & 1 & \vdots \\ a_{n1} & a_{n2} & a_{n3} & a_{n4} & a_{n5} & \cdots & 1 \end{bmatrix} \tag{6}$$

where n = criteria number to be evaluated, C_i = ith criteria, and a_{ij} = importance of ith criteria according to jth criteria.

Step 3 Organize the pairwise comparison in the form of triangle fuzzy numbers using Eq. (1), or they can be given by linguistic terms and use lookup tables (Table 1) to easily derive corresponding values of fuzzy numbers. Before performing all the calculation of the vector of priorities, the comparison matrix (6) has to be normalized by Eq. (7).

$$r_{ij} = a_{ij}{}^{*}\left(\sum_{i=0}^{n} a_{ij}\right)^{-1} \tag{7}$$

$$\begin{bmatrix} r_{11} & r_{12} & r_{13} & \cdots & r_{1n} \\ r_{21} & r_{22} & r_{23} & \cdots & r_{2n} \\ r_{31} & r_{32} & r_{33} & \cdots & r_{3n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ r_{n1} & r_{n2} & r_{n3} & \cdots & r_{nn} \end{bmatrix} \tag{8}$$

Step 4 Check the consistency of judgments across the consistency index CI, random index RI (depends on the size of matrix n, as shown in Table 2), and the consistency ratio CR to reflect the consistency of the decision-maker's judgments during the evaluation phase.

$$\mathrm{CI} = (\lambda_{\max} - N)/(N-1) \tag{9}$$

where $\lambda_{\max}$ and 'N' are successively the principal eigenvalue and the order of the judgment matrix.

The consistency ratio is then calculated using the formula:

$$\mathrm{CR} = \mathrm{CI}/\mathrm{RI} \tag{10}$$

The consistency ratio should be lower than 0.10 to accept the AHP results as consistent. Otherwise, the pairwise comparisons should be revised to reduce inconsistencies.

Step 5 Calculate the weight of the criteria, by calculating the average of the elements of each row from the matrix (8) obtained from step 3.

4 The Proposed Approach

To look for an adequate model combining all the benefits of the OLAP analysis, multi-criteria analysis, and fuzzy logic, it is necessary to establish a representative process when structuring and solving complex decision situations. The stages of the proposed approach are as follows:

4.1 Reflection on Our Decisional Approach

The integration of multi-criteria analysis concepts and fuzzy logic within the OLAP data cube model has several advantages for the decision support that we can summarize below:

- Manage complex decision situations by taking into account all the objective and subjective factors.
- Improve the uncertainty that covers the evaluation of decision-makers' judgments during the data analysis.
- Benefit from the analytical flexibility that OLAP systems can provide to overcome the limitations of MCDA method especially at the time parameter.
- Enrich the data model of the OLAP cube by integrating MCDA concepts and fuzzy set theory.
- Improve the cycle as explained in the following.

4.1.1 Classical Cycle of OLAP Decision Analysis (See Reference [38])

The classical analysis cycle performed by OLAP analysis is based on a single analysis process as explained in Fig. 3.

Table 2 Random index

n	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

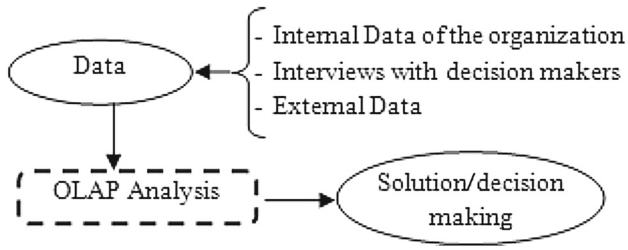


Fig. 3 Classical cycle of the OLAP analysis

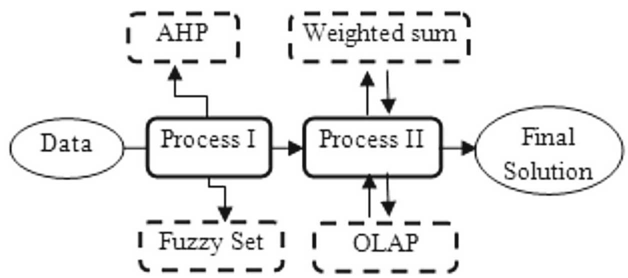


Fig. 4 Enrichment of the OLAP analysis cycle

4.1.2 Enrichment of the Decision Analysis Cycle

In our case, we improve the analysis cycle by introducing a further analysis step that is: AHP method combined with fuzzy set theory in the first analysis process, and weighted sum method integrated in the XML file of the OLAP cube on the second analysis, as mentioned in Fig. 4.

Table 3 Comparative statement of the OLAP and MCDA concepts

Benefits	Limitations
OLAP	
Accessibility of data	Absence of the qualitative aspect in the analysis and management of data
Speed of processing	Lack of structuring complex problems
Dynamic analysis of multidimensional data	
Ability to present the data hierarchy and full details of calculations	
MCDA	
Qualitative and quantitative data analysis	The multi-criteria analyses are often based on slow and iterative process requiring a long time
Manages and simplifies complex situations	Lack of reliable data on time sufficient to establish and validate methods
Useful bargaining tool in discussions between users	

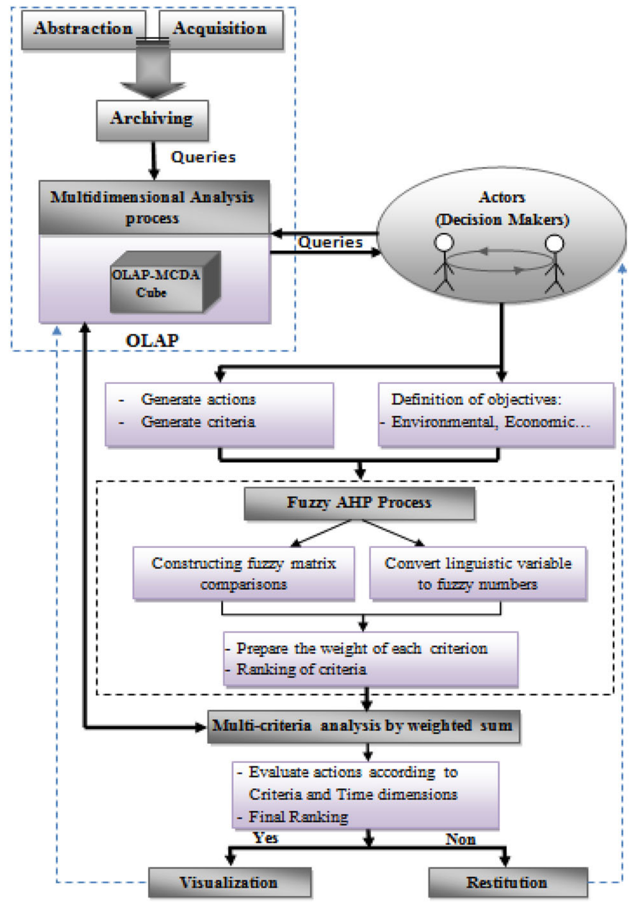


Fig. 5 Followed approach

In Table 3, we summarize, by providing some details, the advantages and limitations of the two main concepts of analysis used in our approach.

4.2 The Methodological Process

To simplify our integrated approach of the data cube model at the OLAP system, we adopt two major processes as explained in Fig. 5:

Process I This process occurs when decision-makers specify all criteria that will determine their favorable choice, proceed firstly to structure these criteria, convert the appreciations assigned by decision-makers to a precise value using fuzzy sets theory, and finally, calculate the importance weight of each criterion.

The major steps to consider in this process are:

- Identification of actions to implement when evaluating.
- Construction of objective (quantitative) and subjective (qualitative) criteria respecting the aspect of heterogeneities in the selection criteria.
- Convert the appreciations assigned to each criterion to precise value.

- Determine the weight of importance for each criterion.

Process II At this stage, the objective is to evaluate and rank the different actions considered in the process through the use of our data cube hybrid model. This process combining the analytical capabilities of OLAP systems with the weighted sum as a multi-criteria decision analysis method will exploit the relative importance/weights of the evaluation criteria obtained from the fuzzy AHP process as input to evaluate and identify the decision alternatives.

The major steps considered in this process are:

- Establish the performance table for the evaluation of the actions, taking into account the selection criteria and time dimension.
- Show the effect of integrating the weighted sum, during the assessment, on the importance of each criterion.
- Rank alternatives using the flexible capabilities of the OLAP analysis.
- Visualize or restitute the final ranking results.

4.3 The Proposed Conceptual Model

We use, in this stage, a conceptual model based on a star-dimensional structure, which offers a fact table (OLAP–MCDA cube) as an evaluation table containing observable, measurable, and digital data [39] surrounded by a single circle of dimensions that include the specific needs of decision-makers as explained below:

Action dimension represents all alternatives, actions, or solutions to evaluate.

Criteria dimension meets all the criteria selected by the decision-makers when defining objectives. These criteria indicate the judgment on the basis on which an action is measured and evaluated.

Time dimension controls the impact and importance of each criterion with respect to each action for a definite period of time.

The conceptual model proposed in Figs. 6 and 7 will be used to construct our cube as explained in Fig. 8.

The cube data (Fig. 8) will be used when integrating the weighted sum function, as an example of multi-criteria analysis method, in the XML file containing the cube OLAP.

The aggregation of the criteria dimension values will be achieved by introducing different weighting in the evaluation process. The criteria chosen concern the three components of sustainable development, i.e., economic, social and environmental.

The weighting can be performed using the formula:

$$u\left(a_i\right) = \sum_{j=1}^{k} v_j . r_{ij} \tag{11}$$

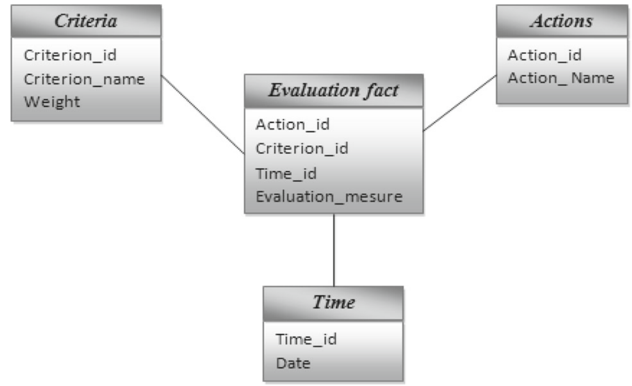


Fig. 6 Multidimensional star schema

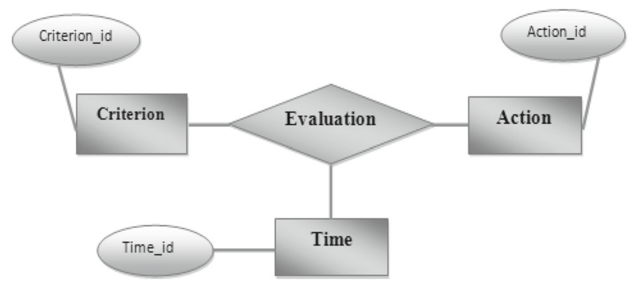


Fig. 7 Entity relationship diagram

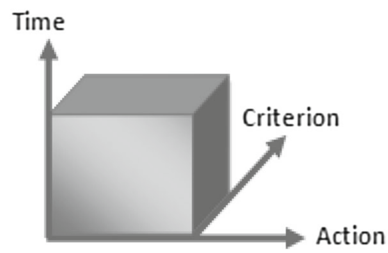


Fig. 8 Abstract representation of the OLAP–MCDA cube

where $u(a_i)$ = utility evaluated of ith alternative, v_j = weight of jth criterion, and r_{ij} = utility evaluated of ith alternative for jth criterion.

5 Empirical Study: Green Logistic for Large Industrial Zones in Casablanca

5.1 Problem Description

In this experiment study, potential itineraries to transport chemicals for large industrial zones located in Casablanca, Morocco, are ranked toward sustainability, using our integration approach. This study considers four itineraries and controls their evolution over a period of time starting from 2000 to 2013 according to the following problem structuring (Fig. 9):

The hierarchical structure used in this decision problem in order to determine the optimal itinerary consists of four

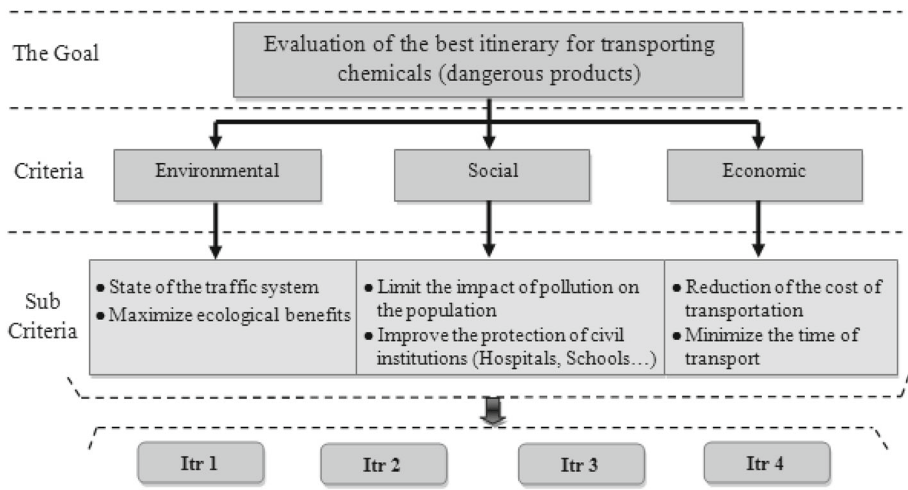


Fig. 9 The hierarchical analysis model of the problem

levels: As shown in Fig. 9, the objective of the problem is situated in the highest level. This goal is divided into three main criteria: environmental (A), social (B), and economic (C), while on the third level, the sub-criteria will be:

SC_A1: State of the traffic system.
SC_A2: Maximize ecological benefits.
SC_B1: Limit the impact of pollution on the population.
SC_B2: Improve the protection of civil institutions (hospitals, schools…).
SC_C1: Reduce the cost of transportation
SC_C2: Minimize the time of transport

The last level of hierarchy includes the solutions of the itineraries to be ranked.

This empirical study aims to achieve the following sub-objectives:

- Reduce the risk of pollution, noise, and explosion hazards of chemicals in the civil area.
- Reduce congestion of the existing road system.
- Ensure a quality logistics service for the industrial zones.
- Contribute to urban policy at the territorial logistics governance.
- Validate our contribution by presenting the results of experiments showing the efficiency and performance of our approach.

5.2 Results and Discussion

At this stage, we present the analysis results of the treatments performed by the fuzzy AHP and TOPSIS processes, and we end by a sensitivity analysis to better assess the risk of decision-makers' perception.

5.2.1 Fuzzy AHP Process

We present in Tables 4, 5, 6, and 7 the comparison matrices of the criteria using a linguistic appreciation technique (fuzzy linguistic variables and triangular fuzzy numbers already defined in Table 1), in order to help the decision-makers in minimizing the margin of uncertainty and simplify the evaluation task.

That is the approximate solution of the feature vector $W = (0.714, 0.193, 0.093)$

With $\lambda_{max} = 3$, the result of consistency using Eqs. (9) and (10) is $CI = 0$; this implies that $CR = 0$, which explains that the fuzzy AHP result can be accepted as consistent for the first hierarchy (main criteria).

Following the same steps of comparison matrices above, we get the results shown in Tables 8, 9, 10, 11, and 12, including the final weight of each criterion and sub-criterion.

The final results of analysis in the first process show that the environmental criteria are the most important in comparison with the other main criteria. This explains that the decision-makers give more attention to environmental

Table 4 Values of the first hierarchy using linguistic variables

Objective	A	B	C
A	EQ	P	G
B	Less P	EQ	WA
C	Less G	Less WA	EQ

Table 5 Comparison matrix using TFN scale

Objective	A	B	C
A	1, 1, 1	3, 5, 7	5, 7, 9
B	1/7, 1/5, 1/3	1, 1, 1	1, 3, 5
C	1/9, 1/7, 1/5	1/5, 1/3, 1	1, 1, 1

Table 6 Comparison matrix using Eqs. (2–5)

Objective	A	B	C
A	0.797, 0.745, 0.652	0.714, 0.789, 0.778	0.714, 0.636, 0.600
B	0.114, 0.149, 0.217	0.238, 0.160, 0.111	0.143, 0.273, 0.333
C	0.089, 0.106, 0.130	0.048, 0.053, 0.111	0.143, 0.091, 0.067

Table 7 Final weight of first hierarchy

Objective	Final weight
A	(0.742, 0.723, 0.677) 0.714
B	(0.165, 0.193, 0.221) 0.193
C	(0.093, 0.083, 0.103) 0.093

Table 9 Evaluation matrix relevant to the A criterion

Sub-criteria	SC_A1	SC_A2
SC_A1	0.250, 0.167, 0.125	0.125, 0.167, 0.250
SC_A2	0.750, 0.833, 0.875	0.875, 0.833, 0.750

Table 10 Evaluation matrix relevant to the B criterion

Sub-criteria	SC_B1	SC_B2
SC_B1	0.833, 0.750, 0.500	0.500, 0.750, 0.833
SC_B2	0.167, 0.250, 0.500	0.500, 0.250, 0.167

Table 11 Evaluation matrix relevant to the C criterion

Sub-criteria	SC_C1	SC_C2
SC_C1	0.167, 0.125, 0.100	0.100, 0.125, 0.167
SC_C2	0.833, 0.875, 0.900	0.900, 0.875, 0.833

impacts, strengthened through the sub-criterion ‘SC_A2’ with an important weight of 0.585 followed by the sub-criterion ‘SC_B1’ (0.134) as a social one. The low importance is given to the economic criteria due to the nature of our case study which is more focused on sustainability. These results can be compared, for example, with others such in [21,22,40] using fuzzy AHP to determine the relative weights of evaluation criteria, and fuzzy TOPSIS or PROMETHEE for ranking alternatives.

5.2.2 OLAP–MCDA Analysis Process

After assigning weights of importance to all criteria using fuzzy AHP process, as explained before, we focus our attention, in this empirical stage of the study, on determining the most appropriate alternative based on our integration process of the weighted sum method within the OLAP analysis.

Our problem consists in selecting the appropriate itinerary (action) to transport chemicals for industrial zones located in Casablanca (Morocco) according to all criteria proposed above. The value of each criterion with respect to each itinerary is controlled during the period 2000–2013. Table 13 contains the transformation for fuzzy membership functions used, for this case, to convert linguistic appreciation to triangular fuzzy numbers when evaluating each itinerary, as also mentioned in Fig. 10.

We provide in Fig. 11 the analysis and modeling of the problem using a multidimensional star schema reflecting the different dimensions mentioned in the proposed conceptual model of our OLAP data cube.

At this stage, we take into consideration the appreciations of decision-makers for each criterion over a definite period of time (Table 14) and proceed to the evaluation and ranking of the four itineraries (Fig. 12).

During all the next steps, we will use JPivot client of Mondrian server [41], which is an open-source OLAP server, to bring multidimensional analysis by drilling and cross-tabulating information. This will help us use XML language and MDX queries for checking information from the XML file containing our OLAP–MCDA cube. This latter has ‘evaluation’ measure, ‘weighted sum’ and ‘multi-criteria aggregation’ as calculated members.

Table 8 Comparison matrix of the sub-criteria (second hierarchy) using linguistic variables

Sub-criteria	SC_A1	SC_A2	SC_B1	SC_B2	SC_C1	SC_C2
SC_A1	EQ	Less P	–	–	–	–
SC_A2	P	EQ	–	–	–	–
SC_B1	–	–	EQ	WA	-	-
SC_B2	–	–	Less WA	EQ	–	–
SC_C1	–	–	–	–	EQ	Less G
SC_C2	–	–	–	–	G	EQ

Table 12 Final ranking of the importance weight for all criteria

Criterion/sub-criterion	Local weight	Global weight	Rank
A	0.714 (0.742, 0.723, 0.677)		
SC_A1	0.181 (0.188, 0.167, 0.188)	(0.139, 0.121, 0.127) 0.129	3
SC_A2	0.820 (0.813, 0.833, 0.813)	(0.603, 0.602, 0.550) 0.585	1
B	0.193 (0.165, 0.193, 0.221)		
SC_B1	0.694 (0.667, 0.750, 0.667)	(0.110, 0.145, 0.147) 0.134	2
SC_B2	0.306 (0.333, 0.250, 0.333)	(0.055, 0.048, 0.074) 0.059	5
C	0.093 (0.093, 0.083, 0.103)		
SC_C1	0.131 (0.134, 0.125, 0.134)	(0.012, 0,010, 0,014) 0.012	6
SC_C2	0.869 (0.867, 0.875, 0.867)	(0.081, 0.073, 0.089) 0.081	4

Table 13 Transformation for fuzzy membership functions

Linguistic term	Triangular fuzzy numbers
Very low (VL)	0.00, 0.10, 0.25
Low (L)	0.15, 0.30, 0.45
Medium (M)	0.35, 0.50, 0.65
High (H)	0.55, 0.70, 0.85
Very high (VH)	0.75, 0.90, 1.00

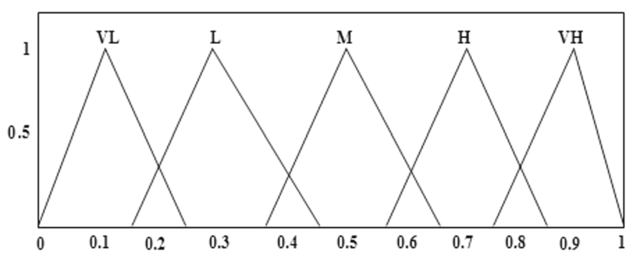


Fig. 10 Graphical representation of linguistic scale for evaluation

Query example 1: Global information (see Fig. 12)

SELECT {[Measures]. [Evaluation]}
ON COLUMNS,
Crossjoin(Crossjoin(
{[itinerary].[All itinerary].Children},{[criteria].[All Criteria].Children}), {[time_by_year].[All Times]})
ON ROWS
FROM [Evaluation]

As explained in the graph below, the decision-makers can vary the level of analysis of the hierarchy around three dimensions: 'criteria', 'itinerary,' and 'time_by_year'. Figure 13 shows a classification of criteria by time for each itinerary.

The effect of the weighting on the importance of each criterion, based on the assessments of all decision-makers (Fig. 14), is evaluated, using Eq. (11), according to the weight of importance already calculated from the fuzzy AHP process of the proposed approach.

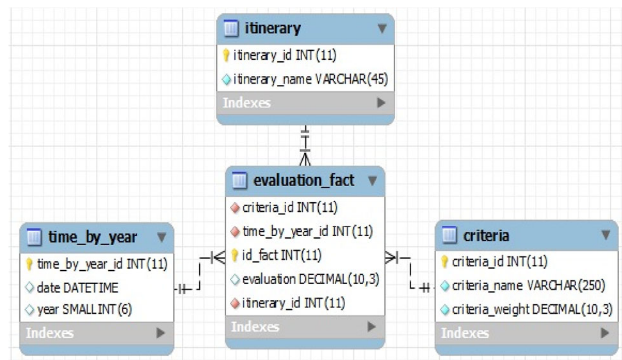
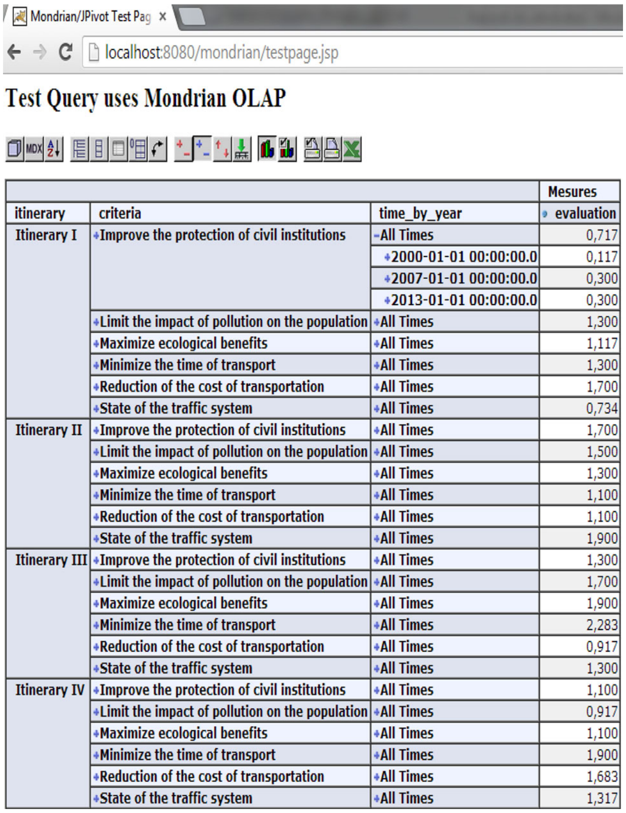


Fig. 11 Star schema of OLAP–MCDA cube

Table 14 Linguistic terms of decision-makers' judgments according to each criterion over a defined period of time

Criteria	Time	I1	I2	I3	I4	Weight
SC_A1	2000	VL	M	L	VL	0.129
	2007	VL	H	M	M	
	2013	M	H	M	H	
SC_A2	2000	VL	L	M	L	0.585
	2007	M	M	H	L	
	2013	M	M	H	M	
SC_B1	2000	L	L	M	VL	0.134
	2007	M	M	M	L	
	2013	M	VH	H	M	
SC_B2	2000	VL	M	L	L	0.059
	2007	L	M	M	L	
	2013	L	H	M	M	
SC_C1	2000	M	L	VL	L	0.012
	2007	M	L	L	M	
	2013	H	M	M	VH	
SC_C2	2000	L	L	H	M	0.081
	2007	M	L	H	H	
	2013	M	M	VH	H	

The new calculated member 'multi-criteria aggregation' is created at the criteria dimension within the OLAP–MCDA



Mondrian/JPivot Test Pag

localhost:8080/mondrian/testpage.jsp

Test Query uses Mondrian OLAP

			Mesures
itinerary	criteria	time_by_year	evaluation
Itinerary I	Improve the protection of civil institutions	All Times	0,717
		2000-01-01 00:00:00.0	0,117
		2007-01-01 00:00:00.0	0,300
		2013-01-01 00:00:00.0	0,300
	Limit the impact of pollution on the population	All Times	1,300
	Maximize ecological benefits	All Times	1,117
	Minimize the time of transport	All Times	1,300
	Reduction of the cost of transportation	All Times	1,700
	State of the traffic system	All Times	0,734
Itinerary II	Improve the protection of civil institutions	All Times	1,700
	Limit the impact of pollution on the population	All Times	1,500
	Maximize ecological benefits	All Times	1,300
	Minimize the time of transport	All Times	1,100
	Reduction of the cost of transportation	All Times	1,100
	State of the traffic system	All Times	1,900
Itinerary III	Improve the protection of civil institutions	All Times	1,300
	Limit the impact of pollution on the population	All Times	1,700
	Maximize ecological benefits	All Times	1,900
	Minimize the time of transport	All Times	2,283
	Reduction of the cost of transportation	All Times	0,917
	State of the traffic system	All Times	1,300
Itinerary IV	Improve the protection of civil institutions	All Times	1,100
	Limit the impact of pollution on the population	All Times	0,917
	Maximize ecological benefits	All Times	1,100
	Minimize the time of transport	All Times	1,900
	Reduction of the cost of transportation	All Times	1,683
	State of the traffic system	All Times	1,317

Fig. 12 Representation of our cube using OLAP JPivot client of Mondrian server

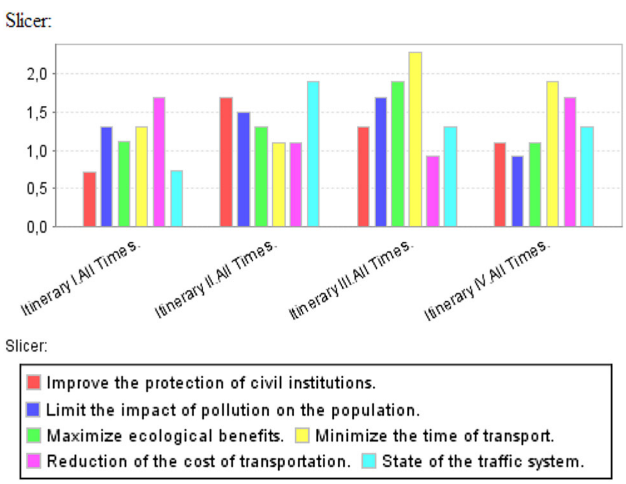


Fig. 13 Criteria evaluation for each itinerary

cube, to allow aggregation of all used criteria according to the method of weighted sum, as shown in Fig. 15.

The representation of the final results after the ranking of multi-criteria aggregation for each itinerary will be made by exploiting analytical mechanisms of OLAP server to move up in the hierarchy of the cube as shown in Fig. 16.

Query example 2: Final solution (see Fig. 16)

WITH
Member [Measures].[Multicriteria Agregation] AS 'Aggregate ([criteria].[All Criteria].Children, [Measures]. [weighted sum])'
SELECT {[Measures].[Multicriteria Agregation]} ON COLUMNS,
{[itinerary].[All itinerary].Children} ON ROWS
FROM [Evaluation]

5.2.3 Analyzing the Results and Sensitivity Analyses

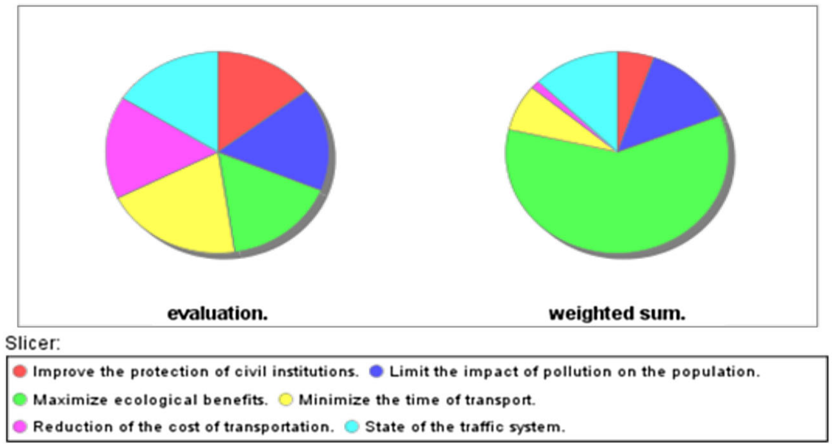
The final ranking of potential itineraries is provided, as shown in Fig. 16, using the graphical representation of the OLAP Mondrian server. In fact, OLAP displays graphically the relative score of each alternative on the basis of the contribution of each selected criterion. In this representation, the most suitable itinerary is the one with the highest score according to the final ranking mentioned in Fig. 16, which revealed that the preferred itinerary was I3 and the second itinerary was I2, followed by I4 and I1.

To measure the influence of decision-makers' risks on the final itinerary ranking, a sensitivity analysis is performed which is illustrated in Table 15 and Fig. 17. The intended objective, as suggested in several contributions [42,43], is to check for the feasible changes that may affect the final rankings provided in Fig. 16 by exchanging each criterion's weight with another. Therefore, fifteen combinations of the six criteria are investigated, with each combination declared as a condition. As mentioned in Fig. 17, the original result of potential itineraries is described as the main condition. For each condition, the multi-criteria aggregations at the OLAP analysis are calculated and their rankings are given. The computational results are summarized in Table 15, and the graphical representations of these results are illustrated in Fig. 17. The comparisons show that the Itinerary 3 remains the best choice in twelve conditions of fifteen. Itinerary 2 is ranked as the secondalternative in eleven conditions. Also, Itinerary 4 is ranked as the third alternative in twelve conditions followed by Itinerary 1 as the last choice in thirteen conditions. The final results of the sensitivity analysis demonstrate that the alternatives' ranking has changed significantly according to equal weights of the criteria, which explains that the found criteria weights consistently form a significant step in the proposed integrated approach. Hence, the conducted sensitivity analysis shows that the weights have impacts on the ranking of alternatives. This will allow decision-makers to improve their decision-making process by adjusting weighting and scoring, and performing sensitivity analyses.

Fig. 14 Effect and result of weighted sum on each criterion

	Mesures	
criteria	evaluation	weighted sum
Improve the protection of civil institutions	4,817	0,284
Limit the impact of pollution on the population	5,417	0,726
Maximize ecological benefits	5,417	3,169
Minimize the time of transport	6,583	0,402
Reduction of the cost of transportation	5,400	0,065
State of the traffic system	5,251	0,677

Slicer:



		Mesures
itinerary	time_by_year	Multicriteria Agregation
Itinerary I	2000-01-01 00:00:00.0	0,155
	2007-01-01 00:00:00.0	0,429
	2013-01-01 00:00:00.0	0,480
Itinerary II	2000-01-01 00:00:00.0	0,306
	2007-01-01 00:00:00.0	0,500
	2013-01-01 00:00:00.0	0,578
Itinerary III	2000-01-01 00:00:00.0	0,459
	2007-01-01 00:00:00.0	0,616
	2013-01-01 00:00:00.0	0,656
Itinerary IV	2000-01-01 00:00:00.0	0,258
	2007-01-01 00:00:00.0	0,346
	2013-01-01 00:00:00.0	0,531

Fig. 15 Aggregated evaluation by year for each itinerary

	Mesures
itinerary	Multicriteria Agregation
Itinerary I	1,090
Itinerary IV	1,175
Itinerary II	1,409
Itinerary III	1,780

Slicer:

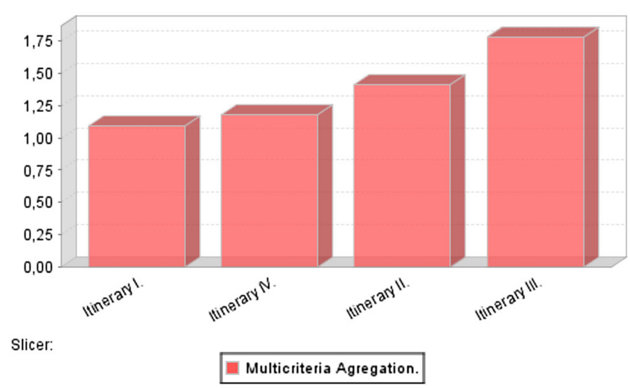


Fig. 16 Final result

6 Conclusion

As a contribution to overcoming difficulties in solving multi-criteria decision situations, a new multidimensional and multi-criteria decision model has been proposed to focus on combining the functionalities of OLAP systems with analytical characteristics of the MCDA methods and fuzzy sets theory. The proposed integrated approach aims at searching an improved solution by optimizing the data model of the OLAP cube, through the construction of two analytical processes integrated in a single one. The fuzzy AHP process

Table 15 Sensitivity analysis

Conditions	Criteria weights						Alternative rankings			
	C1	C2	C3	C4	C5	C6	I1	I2	I3	I4
Main	0.129	0.585	0.134	0.059	0.012	0.081	4	2	1	3
1	0.585	0.129	0.134	0.059	0.012	0.081	4	1	2	3
2	0.134	0.585	0.129	0.059	0.012	0.081	4	2	1	3
3	0.059	0.585	0.134	0.129	0.012	0.081	4	2	1	3
4	0.012	0.585	0.134	0.059	0.129	0.081	4	2	1	3
5	0.081	0.585	0.134	0.059	0.012	0.129	4	2	1	3
6	0.129	0.134	0.585	0.059	0.012	0.081	3	2	1	4
7	0.129	0.059	0.134	0.585	0.012	0.081	4	1	2	3
8	0.129	0.012	0.134	0.059	0.585	0.081	2	3	4	1
9	0.129	0.081	0.134	0.059	0.012	0.585	4	3	1	2
10	0.129	0.585	0.059	0.134	0.012	0.081	4	2	1	3
11	0.129	0.585	0.012	0.059	0.134	0.081	4	2	1	3
12	0.129	0.585	0.081	0.059	0.012	0.134	4	2	1	3
13	0.129	0.585	0.134	0.012	0.059	0.081	4	2	1	3
14	0.129	0.585	0.134	0.081	0.012	0.059	4	2	1	3
15	0.129	0.585	0.134	0.059	0.081	0.012	4	2	1	3
Equal weights	0.167	0.167	0.167	0.167	0.167	0.167	4	1	2	3

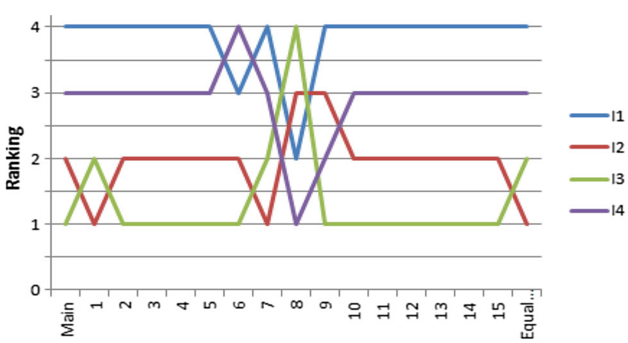


Fig. 17 Sensitivity analysis on the different criteria weights

is used to decompose the decision-making problem into its constituent parts and construct hierarchies of the influential criteria and then identify the relative importance weight for each criterion, while the second process is utilized to aggregate the decision-makers' judgments within the OLAP analysis to rank, prioritize, and select the most suitable solutions. In this paper, the main criteria have been classified into the economic, social, and environmental issues. And the environmental criteria remain the most significant according to the empirical illustration conducted in this article, which reflects the interests of decision-makers focusing on objectives rather than the alternatives.

The analytical capabilities provided by this integrated approach, which is tested on the data model of the OLAP cube, can be used to handle the complexity of multi-criteria decision problems and improve performance in a short period of time. In addition, different multi-criteria techniques such as TOPSIS, PROMETHEE, and VIKOR can be used in this integrated methodology, as in [22,23,27], and comparison of the results can be presented. The main difference we noticed compared to further studies consists at the ability to control the temporal evolution (time dimension's role) of a given problem by taking advantage of the technical and analytical flexibilities that OLAP systems can provide.

In order to make this analytical approach evident and demonstrate how it works, we have applied it on a case study treating the choice of the best itinerary concerning the transport of chemicals for industrial zones located in Casablanca, Morocco. In this context, a sensitivity analysis is performed for the case study to better assess the risk of decision-makers' perception. The results provided are more objective, and the vagueness is quantified and addressed properly.

For forthcoming research, a new integrated methodology combining the present approach with other optimization methods, as mentioned before, will be addressed for better optimizing the process of decision-making when solving complex multi-criteria decision situations, especially in the financial field, which will be an application area that will clearly show the statistical and analytical abilities of OLAP systems.

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