A Fuzzy AHP-TOPSIS Methodology for Selecting the Appropriate Cloud Solution to Manage Big Data Projects

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Abstract:- Recently, the strategic priority of many corporations consists in the creation of competitive advantages by the use of new available technologies, processes and governance mechanisms, such as big data and cloud computing. Since the technology is permanently subject to advances and developments, the question for many businesses is how they can benefit from Big data using the power of technical flexibility that cloud computing can provide. In this paper, we propose a hybrid decision-making methodology based on Affinity Diagram, fuzzy Analytic Hierarchy Process (AHP) and fuzzy Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) to compare, rank and select the most appropriate cloud solutions to accommodate and manage big data projects. The proposed approach consists of four stages. In the first stage, the identification of criteria is performed by a decision-making committee using Affinity Diagram. Due to the varied importance of the selected criteria, a fuzzy AHP process is used to assign the importance weights for each criterion in the second stage, while the TOPSIS process, in stage 3, employs these weighted criteria as input to evaluate and measure the performance of each alternative. In the last step, a sensitivity analysis is performed to evaluate the impact of criteria weights on the final rankings of alternatives.

Key-words:- decision support system, Affinity Diagram, fuzzy AHP, TOPSIS, cloud computing, big data.

1 Introduction

The increasing need of collecting and processing huge quantity of data captured by organizations, such as Internet of Things (IoT) and the rise of social media, is among the reasons leading to the continuous evolution of the enormous developments of architectures commonly referred as big data processing systems and cloud computing. In fact, big data and cloud computing are among the technological revolutions of the time, leading to a major transformation on current IT and imposing significant impacts on scientific research, public administration, and so on. In 2013, the American information technology research (Gartner Inc.) listed the ‘‘Top 10 Strategic Technology Trends For 2013’’ and ‘‘Top 10 Critical Tech Trends For The Next Five Years’’, and big data is listed in both of them. The term big data [1-2] is a collection of data sets so large, moving too fast and complex that it becomes difficult to process with commonly-available tools such as on-hand database management systems or traditional data processing applications. Big data is typically a massive volume of unstructured , semi structured and structured data created from distinct organized and unorganized applications, activities and channels such as digital video, images, sensor data, log files, emails, Tweeter and Facebook, etc. This exponential growth in data [3-4] means that the frontier is vast. So, if we cannot store the data, we can’t analyze them. This is why many organizations notice that the data they own and how they use them can make them distinguished from others. According to the survey in [5], around 50% of 560 enterprises think big data will help them in increasing operational efficiency.

Effectively, the remarkable changes in the manners adopted by researches, businesses and managers are due to the efficient employment of big data analysis. In this context, many efforts have been dedicated to the theme of big data. For example, Weichselbraun *et al*. [6] present a novel methodology for enriching and contextualizing large semantic knowledge bases for opinion mining in big data applications. Renu *et al*. [7] also discuss the use of big data and knowledge discovery to create data backbones for decision support systems. Besides, Yan *et al*. [8] introduce two optimizations process to tackle the inefficiency of the big data processing in terms of large amount of cache misses and stalls of the depended memory accesses. From another perspective, Liang and Lu [9] propose an event driven pipeline and in-memory shuffle design with an improved overlapping of computation and communication for iterative big data computing. Moreover, Dabore and Xhafa [10] analyze and describe all challenges and requirements for next-generation big data services confronted in smart cities, which lead them to present a new platform called 'CAPIM' to collect and aggregate context information on a large scale, and try to assist users, citizens and city officials for a better understanding of traffic problems in large cities.

In the context of this new generation technologies, some other studies have already tried to discuss the subject of moving big data to the cloud, as a new concept, attempting to implement this coupling approach in many different areas. For example, Purcell [11] explains that cloud computing, with its hardware and processing cost reduction, can offer the promise to small and medium sized businesses for big data implementation. Zhang *et al*. [12] propose two algorithms studying the cost-minimizing upload of massive geo-dispersed data for processing into the cloud. Furthermore, Demirkan and Delen [13] describe the possibility of putting analytics and big data in the cloud by demonstrating all the opportunities and challenges of engineering service oriented DSS in the cloud to provide scale, scope and speed economies.

Following these considerations, cloud computing system acts as a required solution in the evolution of Business Intelligence (BI) technologies. As a result, several contributions [14-15] have tried to evaluate and rank the different services provided by these solutions with the aim to select the best one for a well-defined use. As a comparison, the authors in [14] have focused on analyzing the application of Multi-criteria Decision Analysis (MCDA) to service selection in cloud computing without providing any decision-making framework or any methodological analysis to illustrate the effectiveness of their contribution on the selection of cloud computing services. Also, the contribution of Ruiz-Alvarez and Humphrey [15] has interested on the selection of cloud storage service using XML schema to describe the storage systems supported by the different cloud providers, and using only two storage system (Amazon and Azure clouds) as a case study. However, ranking and selecting the most suitable cloud solutions to accommodate and manage big data projects has not received much interest in the decision-making research field, especially solutions with services allowing to transfer and import large amounts of data from other distributed systems such as big data. This causes a dilemma for organization at the level of big data projects, and leads them to ask for the optimal choice, in terms of cloud computing solutions for their computing needs. These reasons have motivated us to propose our integrated approach combining Affinity Diagram with fuzzy AHP and TOPSIS methods with consideration of the specific guidance of the decision-making committee. This approach takes into account technical and e-governmental criteria to be implemented in the proposed methodology, which will enable organizations to achieve competitive gains by migrating, accessing and processing their big data projects using all resources and services of the appropriate cloud.

This work is organized as follows, section 2 presents some related work to the selection problem. Section 3 discusses the advantages of coupling big data and cloud computing. Section 4 briefly explains the proposed methodology followed in order to reach our goal. Finally, section 5 is devoted to empirical study illustrating the effectiveness and performance of our decisional approach. We end the paper by a concluding section.

2 Related Work

The selection problem of cloud computing services is one of the strategic preoccupations that have attracted many researchers **[**14-16-17**]**. With the rapid evolution of decision support systems, the BI experts estimate that putting big data on the cloud has become a real challenge that businesses must take into consideration. For this reason, the selection of cloud solution is considered to be an important research issue for big data projects. However, to the best of our knowledge, only a little bit of attention has been focused on the idea of comparing, ranking and selecting the appropriate cloud solution, as selection problem, to accommodate and access big data projects.

The existing literature work on the selection problem can be classified at least into simulation based approaches, survey based approaches and multi-criteria decision-making based approaches [18]. Most adopted approaches propose frameworks based essentially on AHP, TOPSIS and PROMTHEE methods combined with fuzzy set theory. For instance, Wu [19] has applied FAHP to obtain index weights for community industrial development and uses dynamic programming models and results from the interviews with experts to develop a decision support system. Ardeshir et al. [20] discuss their proposition of selecting and ranking bridge construction sites over rivers by combining fuzzy AHP process with geographic information system. They have employed fuzzy logic to incorporate the uncertainty associated with decision-making into the AHP process when assigning weights, while the geographic information system is used to identify the alternative sites and evaluate the selection criteria. See also [21] integrating geographic information system with AHP to introduce a method for planning forest road network. Other works have integrated fuzzy AHP with other analysis methods especially TOPSIS methodology, such in [22], trying to use FAHP and TOPSIS methods to evaluate the construction projects selection and risk assessment. Shafia and Abdollahzadeh [23] present a new procedure by combining fuzzy TOPSIS and fuzzy KANO techniques in order to firstly identify and classify customer's needs, and secondly rank and categorize the functional requirements in the national standardization system. The contribution of Patil and Kant [24] presents a fuzzy AHP-TOPSIS framework to identify and prioritize the solutions of knowledge management adoption in supply chain. Subsequently, Kilic et al. [25] propose a hybrid methodology combining fuzzy AHP with TOPSIS method for the selection of ERP systems. Similarly, KARAMI and JOHANSSON [26] use Bayesian networks, sensor allocation, TOPSIS and AHP methodologies to integrate automatic and manual ranking of options. The fuzzy AHP combined with PROMETHEE methodology is then used in [27] to evaluate power substation location. We also quote the integration of Analytic Network Process (ANP) and PROMETHEE firstly illustrated in [28] to select the best material for a given application, and in [29] for better addressing the ERP selection problem.

3 Big data on the cloud

As Tim Byers of Motley Fool explains in an interview at the March 2013 South by Southwest (SXSW) Conference, that "big data and cloud computing are becoming one in the same - cloud resources are needed to support big data storage and projects, and big data is a huge business case for moving to cloud". In fact, as big data needs a lot of compute and massive storage, many enterprises work today on how they can use the power of technique flexibility provided by cloud computing to benefit from big data. Indeed, the link between these two technologies as noticed in [30], is explained by the fact that big data can provide the ability to use commodity computing for processing distributed queries through multiple data sets and return, in a timely manner, the resultant sets. On the other side, cloud computing provides the underlying engine across the use of Hadoop as a class of distributed data-processing platforms which is also known for bringing speed to innovation, rapid scalability and agility, and a lower total cost of ownership to this relationship. More precisely, as discussed in [31], cloud computing provides an infrastructure that can serve as an effective platform to address the variety and complexity of data types in order to perform big data analysis. In this context, Bollier [32] highlighted the ability and potential of cluster computing to supply a hospitable background for data growth. Nevertheless, the lack of data availability, as Miller argued in [33], with an incorrect use of the analytical methods when treating offloaded decision may generate wrong and costly decisions. At this point, shipping all enterprise data to the cloud has become easier and faster using cloud provider import services. In fact, any enterprise can ship its disks containing its data directly to the cloud providers, and then, those data will be loaded in one of their data centers. This last operation must follow the same security practices when storing data online in the cloud.

3.1 Key Players in the Cloud Computing Environment

In the following, we propose a list of some key players that are currently leaders in the field of cloud computing. We also cite some of their main characteristics and contributions in terms of products, innovations or new services, especially service of transferring and importing large amounts of data. We have made the list shorter, but have tried to be eclectic at the same time. Our aim is to highlight some key players that incorporate tools of migrating and transferring data in their cloud products. Those tools will significantly help in reducing the time requirements as well as the potential network impact, which clearly show the difference between weeks and months versus days to get data into the cloud.

The proposed cloud solutions are indicated as follows:

Amazon : It has undoubtedly been one among the pioneers in the cloud arena, offering pay-as-you-go access to virtual servers and data storage space. Its Amazon Web Services offers include the Elastic Compute Cloud (EC2), for computing capacity, and the Simple Storage Service (S3), for on-demand storage capacity. In addition to these core offerings, Amazon offers a database Web service (SimpleDB); a Web service for content delivery (CloudFront); and the Simple Queue Service (a hosted service for storing messages as they travel between computers). Amazon has developed **AWS Import/Export**

service used for transferring large amounts of data from physical storage devices into AWS. This transfer is made directly to and from storage devices through the Amazon‘s high-speed internal network and bypassing the Internet. For significant data sets, AWS Import / Export is often faster than Internet transfer and more cost effective than upgrading the connectivity. Data migration, content delivery and direct data exchange are among the common use cases of the AWS Import / Export.

HP Cloud: It offers many cloud services all available from Hewlett Packard organization (HP). It represents the combination of the anterior HP Converged Cloud business unit and HP Cloud Services, which is the OpenStack technology. HP Helion Public Cloud, as a new feature, is committed to delivering leading edge public cloud infrastructure, platform services, and cloud solutions for developers, ISVs, partners, service providers, and enterprises. **HP Bulk Import** is a new service provided by HP Cloud for reducing the time to market for applications requiring existing data by allowing users to easily and quickly load their data into HP Cloud Block Storage or HP Cloud Object Storage. Like the other services, HP bulk import let users send and provide hard drives directly to HP’s data center, where data can be rapidly uploaded and transferred.

Google: No one knows the Internet quite like Google. It is the fastest growing cloud provider today, its foray into software-as-a-service applications for businesses is hastening the industry's move from packaged software to Web-hosted services. It was doing a bunch of stuff in the cloud including running a popular PaaS called Google App Engine, offering Google Cloud Storage and launching a new big data cloud app, Google BigQuery. Using the Offline Disk Import, **Google cloud storage** help organizations to transfer their data set by sending Google physical hard drives that it loads into an empty cloud storage bucket. The data must be encrypted because it’s loaded directly into Google’s network. This option can be helpful for organizations if they are limited to a slow, unreliable, or expensive Internet connection.

Rackspace: It has a long history of offering hosted data center services and is a trusted name in the enterprise. It helps organizations create the infrastructure that performs best for their business. Rackspace consists of three major services: Cloud Servers, an Amazon EC2-like service that provides access to virtualized server instances; Cloud Files, a storage service; and Cloud sites, a platform for building Web sites. **Rackspace bulk import** for cloud files is a simpler way to get a lot of data into the cloud by sending Rackspace physical media to be uploaded directly at the data centers, where “migration specialists” connect the device to a workstation that has a direct link to Rackspace’s cloud files infrastructure. Rackspace provides continuous updates on the progress of the device and its data, and a dedicated migration specialist offers Fanatical Support the whole way through.

Aspera: It is presented as a leader in high-speed delivery of data to the cloud. It is used in cases where the data is too large to transmit and access demands which will not allow the latency inherent in shipping data. Aspera offers several services such as the Aspera On-Demand Transfer Solutions which bring cost savings and efficiency gains to organizations. It is used to move large volumes of data into, out of and within the cloud storage and computing environments. Microsoft Windows Azure, Amazon AWS and Google are among the partners who have already signed a contract to use the Aspera On-Demand Transfer Solutions.

4 The Proposed Methodology

Many methods of multi-criteria decision analysis have been proposed in order to help the decision makers to take the most adequate choice for their own decisions. These methods can be classified into two approaches: methods of the unique approach of synthesis such as SMART, TOPSIS, MAUT, MAVT, WEIGHTED SUM, UTA, AHP, and the outranking methods of synthesis as ELECTRE, PROMETHEE and MACBETH. In this paper, we have chosen fuzzy AHP method thanks to its ability to decompose the decision-making problem into its constituent parts, and assign the importance weight to the influential criteria already identified by a decision-making committee using the Affinity Diagram. Concerning the process of ranking alternatives, we have chosen the TOPSIS method due to its logical reasoning in representing the rationale of human choice using a simple computation process, which combines both positive and negative criteria when evaluating and measuring the performance of complex alternatives.

Our approach uses three major processes as explained below (Figure 1):

Process I: This process occurs when the decision-making committee describes the problem using the Affinity Diagram and proceeds to generate ideas about all criteria needed to be considered when making the decision. It is ended when a consensus is reached for the selected criteria.

Process II: The FAHP process, which handles the vagueness inherent in the decision making process, proceeds firstly to structure hierarchically the specified criteria and convert the appreciations of decision makers assigned to each criterion to a precise value by the use of fuzzy set theory, then finally, calculate the relative importance/weights of these criteria.

Process III: The objective of this process is to evaluate and rank different alternatives considered in the decision making process benefiting from the technical performance of the TOPSIS method. The weighted criteria obtained from the FAHP process are then considered as input to calculate the weighted normalized matrix in this process, which will allow us to determine the positive ideal solution and negative ideal solution, and then, identify the candidate alternative of the final ranking. At the end of this process, a sensitivity analysis is performed in order to measure the effect of criteria weights on the decision making process.

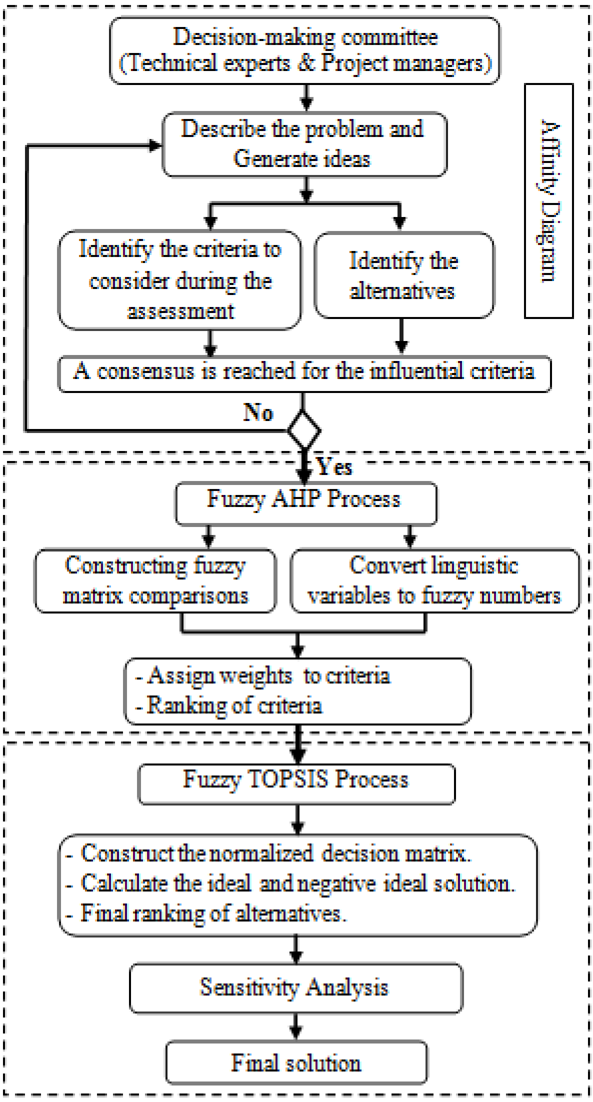

Fig.1. The followed approach

4.1 Affinity Diagram

An Affinity Diagram also called the KJ method, after its developer Kawakita Jiro, is a tool to synthesize and generate groupings of data by finding relationships between ideas gathered through interviews, survey, or feedback results. The information is then structured gradually from the bottom up into meaningful groups. Ishikawa recommends using the Affinity Diagram when thoughts or facts are unclear and need to be organized.

The different steps of Affinity Diagram adapted from [34] are defined as follows:

- Describe the problem and precise it in easily understandable way to the team members.
- Generate ideas by brainstorming. The team members have to write each idea on a separate note cards and put these on a wall or flip chart.
- Sort ideas into natural themes by asking about the similarity of ideas and if they are connected to any of the others.
- Create total group consensus by moving the cards into groups with a similar theme. If you disagree with a placement of a card move it silently in the proper group.
- A consensus is reached when all cards are in groups and team members have stopped moving the cards.
- Create header cards when the consensus is reached and all cards are in the right groups.
- Finalize the Affinity Diagram and provide a working document to all participants.

4.2 Fuzzy AHP

The Analytic hierarchy Process (AHP), initially introduced by Saaty [35], has becomes a powerful and flexible methodology in solving complex decision situations. In fact, the AHP process consists in representing a decision problem by a hierarchical structure reflecting the interactions between the various elements of the problem, then using pair-wise comparison judgments to identify and estimate the relative importance of criteria and alternatives.

However, the AHP method has some shortcomings [36] due to its ineffectiveness when applied to an ambiguous problem. Indeed, 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 by natural language. This is why several researches such as [19-20][22][24-25][37] and many others, introduce fuzzy logic into the pair-wise comparison of the AHP to compensate and deal with this type of fuzzy decision problem.

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:

Definition1: A fuzzy set A of an universe of discourse X is characterized by a membership function μ_A:

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

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

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

Fuzzy set theory is used to model the uncertainty and imprecision in decision making processes resulting due to lack of complete information [18].

Definition 2: A membership function of a triangular fuzzy number M can be defined by a triplet *(a, m, b)* as follows:

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

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

The basic operations on Fuzzy triangular numbers are as follows:

Addition:

$$(a_1, m_1, b_1) + (a_2, m_2, b_2) = (a_1 + a_2, m_1 + m_2, b_1 + b_2) \quad (2)$$

Multiplication:

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

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:

$$(a_1, m_1, b_1)^{-1} = (1/b_1, 1/m_1, 1/a_1) \quad (5)$$

For $a_1, a_2 > 0;\ m_1, m_2 > 0;\ b_1, b_2 > 0$

Considering the above-mentioned fuzzy theory, the proposed fuzzy AHP procedure is then defined as follows:

Step 1: The problem is 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 this goal are in the lower levels.

Step 2: The comparison matrices are built by conducting pair-wise comparisons of the elements of each hierarchical level with respect to an element of the upper hierarchical level.

$$\begin{array}{c} \\ C_1 \\ C_2 \\ C_3 \\ C_4 \\ . \\ C_n \end{array} \begin{array}{c} \begin{array}{ccccccc} C_1 & C_2 & C_3 & C_4 & C_5 & . & C_n \end{array} \\ \begin{pmatrix} 1 & a_{12} & a_{13} & a_{14} & a_{15} & . & a_{1n} \\ a_{21} & 1 & a_{23} & a_{24} & a_{25} & . & a_{2n} \\ a_{31} & a_{32} & 1 & a_{34} & a_{35} & . & a_{3n} \\ a_{41} & a_{42} & a_{43} & 1 & a_{45} & . & a_{4n} \\ . & . & . & . & . & 1 & . \\ a_{n1} & a_{n2} & a_{n3} & a_{n4} & a_{n5} & . & 1 \end{pmatrix} \end{array} \qquad (6)$$

Where

n = criteria number to be evaluated.

C_i = i^{th} criteria.

a_{ij} = importance of i^{th} criteria according to j^{th} criteria.

Step 3: The pair-wise comparisons are organized in the form of fuzzy triangle numbers using Eq. (1), or they can be given by linguistic terms, and use look-up table (Table 1) to easily derive corresponding values of fuzzy numbers. Before performing all the calculation of vector of priorities, the comparison matrix (6) has to be normalized by Eq. (7).

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

$$\begin{pmatrix} r_{11} & r_{12} & r_{13} & \dots & r_{1n} \\ r_{21} & r_{22} & r_{23} & \dots & r_{2n} \\ r_{31} & r_{32} & r_{33} & \dots & r_{3n} \\ .. & .. & .. & & \\ r_{n1} & r_{n2} & r_{n3} & & r_{nn} \end{pmatrix} \qquad (8)$$

Table 1. Pairwise comparison scale (see ref [38])

Linguistic Term	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 (L.WA)	(1/5, 1/3, 1)
Less P (L.P)	(1/7, 1/5, 1/3)
Less G (L.G)	(1/9, 1/7, 1/5)
Less VG (L.VG)	(1/9, 1/9, 1/7)

Step 4: The consistency of judgments is checked across the consistency index *CI*, random index *RI* and the consistency ratio *CR* to reflect the consistency of the decision maker's judgments during the evaluation phase.

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

Where

λ_{max} = Principal eigenvalue of the judgment matrix

N = the order of the judgment matrix.

The consistency ratio is then calculated using the formula:

$$CR = CI/RI \qquad (10)$$

The relevant index should be lower than 0.10 to accept the AHP results as consistent. Otherwise, the pair-wise comparisons should be revised to reduce inconsistencies.

Step 5: The final weight of each criterion is obtained by calculating the average of the elements of each row from the matrix (8) obtained from step 3.

4.3 Fuzzy TOPSIS

The Technique for Order Preference by Similarity to Ideal Solution which is known as TOPSIS was developed by Hwang and Yoon [39] to identify solutions from a finite set of alternatives. Its underlying logic is to define the positive ideal solution and negative ideal solution. In fact, the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. In the classical formulation of the TOPSIS method, the ratings and the weights of criteria are measured in crisp values. However, measurement by using crisp numbers is not always possible and inadequate to deal with the vagueness and imprecision of human judgments. In this context, the use of linguistic terms rather than crisp value may be a better approach to cover this uncertainty. For this reason, we extend the concept of TOPSIS method to develop a suitable methodology dealing with human life application problems under a fuzzy environment [23, 24 and 40] as explained below:

Step 1: Establish a decision matrix using linguistic variables with triangular fuzzy numbers, which is shown in Tables 1 and 6, for ratings '*m*' alternatives with respect to each criterion ('*n*' criteria) as given below:

$$y = (g_{ij})_{mxn} = \begin{array}{c} \\ g_1 \\ g_2 \\ .. \\ g_n \end{array} \begin{array}{c} \begin{array}{cccc} c_1 & c_2 & \dots & c_n \end{array} \\ \begin{bmatrix} g_{11} & g_{12} & \dots & g_{1n} \\ g_{21} & g_{22} & & g_{2n} \\ .. & & & \\ g_{m1} & g_{m2} & & g_{mn} \end{bmatrix} \end{array} \qquad (11$$

Where

$g_1, g_2, \dots, g_m$ = Feasible alternatives

$c_1, c_2, \dots, c_n$ = Evaluation criteria

g_{ij} = The rating given to alternative g_i against criterion c_j

Step 2: Construct the normalized decision matrix. The normalized value r_{ij} is calculated as follows:

$$r_{ij} = g_{ij} / [\sum_{i=1}^{m}(g_{ij})^2]^{1/2} \qquad (12$$

Step 3: Calculate the weighted normalized decision matrix v_{ij} as given below:

$$v_{ij} = w_j\, r_{ij} \qquad (13$$

w_j is the weight of criterion c_j

Step 4: Determine the positive ideal and negative ideal solution from the weighted normalized decision matrix.

$$A+ = \begin{cases} Max\ v_{ij} \mid g_i \in G^1 \\ 1 \le j \le n \\ Min\ v_{ij} \mid g_i \in G^2 \\ 1 \le j \le n \end{cases} \qquad (14$$

$$A- = \begin{cases} Min\ v_{ij} \mid g_i \in G^1 \\ 1 \le j \le n \\ Max\ v_{ij} \mid g_i \in G^2 \\ 1 \le j \le n \end{cases} \qquad (15$$

Where G^1 is the set of benefit criteria, and G^2 is the set of cost criteria.

Step 5: Calculate the Euclidean distance (D_i) for each alternative '*i*' between positive ideal solution and negative ideal solution.

$$D_i^+ = [\sum_{j=1}^{n}(v_{ij} - v_j^+)^2]^{½} \qquad (16$$

$$D_i^- = [\sum_{j=1}^{n}(v_{ij} - v_j^-)^2]^{½} \qquad (17$$

Step 6: Calculate the relative closeness (C_i) to the ideal solution of each alternative as follows:

$$C_i = D_i^- / (D_i^+ + D_i^-) \qquad (18$$

Step 7: Rank alternatives in decreasing order according to the closeness coefficient C_i, the most appropriate alternative should have the "shortest distance" from the positive ideal solution and the "farthest distance" from the negative ideal solution.

5 Empirical Illustration: Which Cloud for your Big Data?

The objective of this numerical illustration, as explained before, is to investigate the ranking and selection of the most suitable cloud solutions in terms of all the services offered to manage big data projects. This will allow decision makers to facilely access, migrate and analyze their big data through the use of cloud computing resources. The rise of cloud computing has been a precursor and facilitator to the emergence of big data. However, cloud platforms take many forms and sometimes need to be integrated with traditional architectures.

In this section, we propose a hierarchical structure consisting of four levels to determine the optimal cloud solution: as shown in Figure 2. The objective is shown in the highest level of the hierarchy. Concerning the selection of evaluation criteria, a committee of decision makers (decision makers, experts and project manager) are former in order to identify and generate criteria for evaluating cloud solutions. The final list includes three main criteria (second level) and ten sub-criteria (third level). The three main criteria can be classified into e-governance, business continuity and security respectively, while the sub-criteria are organized as follows:

C1: Monitoring system and management transparency.
C2: Ability to rapidly launch new products and services.
C3: Possibility to transfer and/or import data.
C4: IT capital expenditures.
C5: On-demand capacity.
C6: Guarantee for high availability.
C7: Implementation cost.
C8: Confidentiality.
C9: Incident management.
C10: Data segregation and encryption.

The last level of hierarchy includes alternatives which represent a specimen of five different products of cloud solutions as follows: CL1, CL2, CL3, CL4 and CL5.

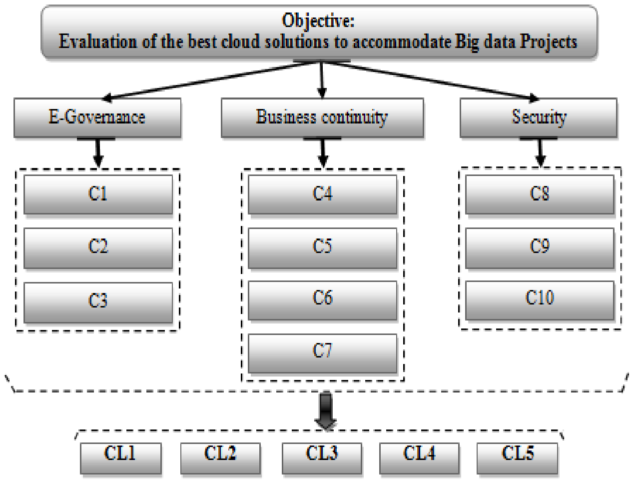

Fig.2. The hierarchical analysis structure of the problem

5.1 Generation of criteria weight using fuzzy AHP

After specifying all the needed criteria by the decision-making committee, we focus at this stage on calculating the relative importance/weights of those criteria. Note that the number of the involved decision makers (DMs) is limited to three. In this context, the required pair-wise comparison matrices for each decision maker (DM) using Eqs. (1-5) and Table 1 for linguistic variables and TFN scales are presented in Tables 2-4 as follows.

Table 2. Comparison matrix for the main criteria using TFN scale

Objective	E-gov			B. cont			Security		
	DM_1	DM_2	DM_3	DM_1	DM_2	DM_3	DM_1	DM_2	DM_3
E-gov	EQ	EQ	EQ	WA	P	L. WA	P	P	WA
B. cont	L.WA	L.P	WA	EQ	EQ	EQ	WA	L.WA	P
Security	L.P	L.P	L.WA	L.WA	WA	L.P	EQ	EQ	EQ

Table 3. The evaluation matrix for the main criteria

Objective	E-gov	B. cont	Security
E-gov	(1, 1, 1)	(0.2, 2.778, 7)	(1, 4.333, 7)
B. cont	(0.143, 0.360, 5)	(1, 1, 1)	(0.2, 2.778, 7)
Security	(0.143, 0.231, 1)	(0.143, 0.36, 5)	(1, 1, 1)

Table 4. Final weight of first hierarchy

Objective	Final weight	
E-gov	(0.460, 0.611, 0.383)	0.485
B. cont	(0.316, 0.270, 0.419)	0.335
Security	(0.224, 0.118, 0.198)	0.180

That is, the approximate solution of the feature vector W= (0.485, 0.335, 0.180).

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 AHP result can be accepted as consistent for the first hierarchy of the main criteria.

Following the same steps of comparison matrices above, we get the results shown in Table 5 including the weight of each criterion and sub criterion.

Table 5. Final criteria weight.

Criterion/Sub-criterion		Local weight	Global weight	Rank
E-gov		(0.460, 0.611, 0.383) 0.485	-	-
	C1	(0.131, 0.106, 0.121)	(0.060, 0.065, 0.046) 0.057	5
	C2	(0.261,0.260, 0.319)	(0.120, 0.159, 0.122) 0.134	3
	C3	(0.608, 0.634, 0.560)	(0.289, 0.387, 0.214) 0.297	1
B. cont		(0.316, 0.270, 0.419) 0.335	-	-
	C4	(0.123,0.133,0.151)	(0.039, 0.036, 0.063) 0.046	7
	C5	(0.057,0.125,0.162)	(0.018, 0.034, 0.068) 0.040	8
	C6	(0.719,0.629,0.555)	(0.227, 0.170, 0.233) 0.210	2
	C7	(0.100,0.113,0.133)	(0.031, 0.031, 0.056) 0.039	9
Security		(0.224, 0.118, 0.198) 0.180	-	-
	C8	(0.317, 0.283, 0.341)	(0.071, 0.033, 0.068) 0.057	5
	C9	(0.088, 0.074, 0.068)	(0.020, 0.009, 0.013) 0.014	10
	C10	(0.597, 0.643, 0.591)	(0.134, 0.076, 0.117) 0.109	4

The final results of the first process (Table 5) taking into account all judgments of decision makers show that the e-governance criteria have the most important influence (0.485) when compared to the other main criteria. The reason of giving more attention to the e-governance criteria is that the decision makers are mainly interested in increasing the flexibility of governance and monitoring for a company when using a distributed decision system such as cloud computing. The global weight of all sub-criteria 'C3: 0.297', 'C2: 0.134' and 'C1: 0.057' explains this interests followed by the business continuity criteria (0.335), which ensure the high availability of data, and finally security criteria (0.180) for encrypting those data.

These analysis results can be compared, for example, to other methodologies dealing with the selection problems such in [26, 28, 29] using fuzzy AHP as a procedure to determine the relative weights of evaluation criteria, and fuzzy PROMETHEE or TOPSIS for ranking alternative.

5.2 Evaluation and selection of Alternatives using fuzzy TOPSIS

As explained in the proposed methodology, the weights of importance assigned to all criteria using FAHP will be used as input in the fuzzy TOPSIS process to evaluate and rank alternatives.

The computational procedure to follow during this proposed process is summarized as explained below:

Step 1: The decision making group use the linguistic variables with (TFN) numbers to evaluate the importance of the criteria and alternatives which is shown in Figure 3 and Table 6. The rating of alternatives with respect to each criterion (Eq. (11)) will be performed using the linguistic rating variables. The rating of the 5 alternatives by decision makers under 10 criteria is shown in Table 7.

Step 2: The normalized decision matrix will be constructed (Eq. (12)), as mentioned in Table 8, on the basis of the performance ratings of the 5 alternatives (Table 7).

Step 3: The weighted normalized decision matrix is constructed (Eq. (13)) as in Table 9 using the importance weights of the criteria already calculated from FAHP process in Table 5.

Step 4: The positive ideal solution and negative ideal solution is performed (Eqs. (14) & (15)) as shown in Table 10 taking into consideration the benefit criteria (Bnf_C) and the cost criteria (Cst_C).

Step 5: The relative distance D_i^+ and D_i^- of each alternative from positive and negative ideal solution with respect to each criterion will be calculated (Eqs. (16) & (17)) as explained in Table 11.

Step 6 & 7: The closeness coefficient of each alternative (cloud solution) will be determined (Eq. (18)) using the relative distance (D_i^+ and D_i^-). The final ranking of the alternatives depending on the descending order of closeness coefficient is shown in Table 11.

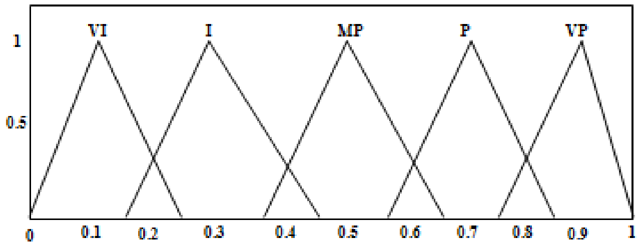

Fig.3. Linguistic rating variable for evaluation

Table 6. Linguistic scales for the importance

Linguistic Term	Triangular fuzzy number (TFN)
Very Insufficient (VI)	(0.00, 0.10, 0.25)
Insufficient (I)	(0.15, 0.30, 0.45)
Medium Importance (MP)	(0.35, 0.50, 0.65)
Important (P)	(0.55, 0.70, 0.85)
Very Important (VP)	(0.75, 0.90, 1.00)

Table 7. Decision-maker's rating of the 5 alternatives under 10 criteria.

Alternative	Criteria									
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
Weight	0.057	0.134	0.297	0.046	0.040	0.210	0.039	0.057	0.014	0.109
Bnf_C/Cst_C	Bnf_C	Bnf_C	Bnf_C	Cst_C	Bnf_C	Bnf_C	Cst_C	Bnf_C	Bnf_C	Bnf_C
CL1	MP	I	P	VI	P	P	I	MP	P	I
CL2	I	MP	MP	P	VP	P	MP	VI	I	MP
CL3	P	VP	P	I	I	VI	MP	P	P	I
CL4	P	VI	I	P	MP	P	I	MP	MP	P
CL5	VI	I	P	P	I	MP	VI	P	I	MP

Table 8. Normalized decision matrix (r_{ij})

Alternative	Criteria									
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
CL1	0,216	0,084	0,364	0,011	0,386	0,372	0,108	0,205	0,413	0,083
CL2	0,078	0,234	0,186	0,391	0,546	0,372	0,300	0,011	0,076	0,231
CL3	0,424	0,651	0,364	0,072	0,071	0,010	0,300	0,401	0,413	0,083
CL4	0,424	0,013	0,067	0,391	0,197	0,372	0,108	0,205	0,211	0,453
CL5	0,012	0,084	0,364	0,391	0,071	0,190	0,016	0,401	0,076	0,231

Table 9. Weighted normalized decision matrix (v_{ij})

Alternative	Criteria									
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
CL1	0,012	0,011	0,108	0,001	0,015	0,078	0,004	0,012	0,006	0,009
CL2	0,004	0,031	0,055	0,018	0,022	0,078	0,012	0,001	0,001	0,025
CL3	0,024	0,087	0,108	0,003	0,003	0,002	0,012	0,023	0,006	0,009
CL4	0,024	0,002	0,020	0,018	0,008	0,078	0,004	0,012	0,003	0,049
CL5	0,001	0,011	0,108	0,018	0,003	0,040	0,001	0,023	0,001	0,025

Table 10. Positive and negative ideal solution.

Ideal solution	Criteria									
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A^+	0,024	0,087	0,108	0,001	0,022	0,078	0,001	0,023	0,006	0,049
A^-	0,001	0,002	0,020	0,018	0,003	0,002	0,012	0,001	0,001	0,009

Table 11. The related closeness coefficients (C_i) and the final ranking.

Alternatives	Distance D_i^+	Distance D_i^-	Closeness coefficient C_i	Final Ranking
CL1	0,08775	0,12025	0,578	2
CL2	0,08852	0,09239	0,511	4
CL3	0,08881	0,12800	0,590	1
CL4	0,12549	0,09030	0,418	5
CL5	0,09512	0,10092	0,515	3

Table 12. Sensitivity analysis

Experiments	Gradual variation in the criteria weight										Performance scores (C_i)				
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	**CL1**	**CL2**	**CL3**	**CL4**	**CL5**
Main	0,057	0,134	0,297	0,046	0,04	0,21	0,039	0,057	0,014	0,109	0,578	0,511	0,590	0,418	0,515
1	0,297	0,134	0,057	0,046	0,04	0,21	0,039	0,057	0,014	0,109	0,490	0,415	0,632	0,624	0,252
2	0,057	0,297	0,134	0,046	0,04	0,21	0,039	0,057	0,014	0,109	0,348	0,440	0,689	0,316	0,270
3	0,057	0,134	0,046	0,297	0,04	0,21	0,039	0,057	0,014	0,109	0,613	0,393	0,594	0,386	0,257
4	0,057	0,134	0,04	0,046	0,297	0,21	0,039	0,057	0,014	0,109	0,555	0,361	0,697	0,417	0,229
5	0,057	0,134	0,21	0,046	0,04	0,297	0,039	0,057	0,014	0,109	0,593	0,489	0,593	0,520	0,461
6	0,057	0,134	0,039	0,046	0,04	0,21	0,297	0,057	0,014	0,109	0,521	0,438	0,434	0,532	0,506
7	0,057	0,134	0,057	0,046	0,04	0,21	0,039	0,297	0,014	0,109	0,490	0,389	0,624	0,498	0,568
8	0,057	0,134	0,014	0,046	0,04	0,21	0,039	0,057	0,297	0,109	0,595	0,411	0,606	0,479	0,262
9	0,057	0,134	0,109	0,046	0,04	0,21	0,039	0,057	0,014	0,297	0,395	0,499	0,420	0,590	0,387
Equal weight	0,100	0,100	0,100	0,100	0,100	0,100	0,100	0,100	0,100	0,100	0,572	0,418	0,524	0,445	0,375

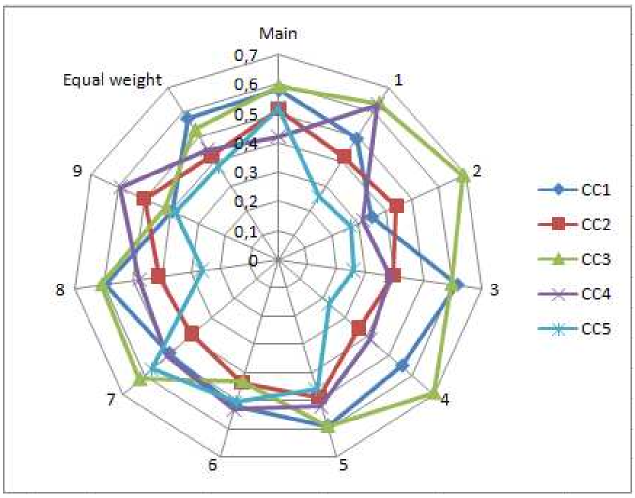

Fig.4. Final results of sensitivity analysis (C_i scores)

5.3 Sensitivity analysis

By comparing the closeness coefficient C_i values of the five alternatives as shown in Table 11, we conclude that CL3 > CL1 > CL5 > CL2 > CL4. Thus, alternative CL3 is selected as the best appropriate cloud solution and recommended for implementation.

To measure the impact of criteria weights on the selection of the appropriate cloud solutions, we conducted the sensitivity analysis illustrated in Table 12. The objective, as suggested in several contributions [18, 41, 42- 43], is to investigate the sensitivity of the final decision to small variations in the criteria weights attributed during the comparison process. It is performed by changing slightly the values of the weights and observing the influence on the decision. Thus, ten experiments were conducted. Table 12 presents the details of these experiments, and the graphical representations of these experiments results are shown in Figure 4.

The comparisons show that CL3 remains the best choice in practically all experiments except experiments 3, 6 and 9, on which the highest criterion weight (0,297) is given respectively to C4, C7 and C10 for the three experiments. CL1 shares the first and second ranking when seven experiments are executed, which makes it closer to its original ranking illustrated in Table 11. Also, CL4 is ranked as the third choice by exchanging its original ranking with that of CL5, followed by CL2 and finally CL5 as the last choice. It should be taken into account that the result of evaluation of the alternatives is based on e-governance, security and business continuity points (Figure 2 and Table 5). Among these, the e-governance criterion is most important followed by business continuity and security ones.

The sensitivity analysis result proves that the alternatives' ranking has changed considerably depending on equal weights of the criteria. This explains that the weights of criteria found systematically form an important step in our integrated approach. Therefore, the carried sensitivity analysis indicates that weights have implications on the ranking of alternatives, which will allow the decision-making committee to increase their decision-making process by adapting weighting and scoring, and then performing sensitivity analyses.

6 Conclusion

The objective of this study is to present a decision analysis methodology based on Affinity Diagram and fuzzy AHP-TOPSIS to evaluate, rank and select the most adequate cloud solution to access and process big data projects. In a decision-making situation, the decision makers often deal with the selection problem on the basis of a set of multiple and conflicting criteria. The consideration of these criteria affects directly the performance and service productivity of a company. Thus, we need to recognize influential criteria that have an impact on the evaluation and selection of the appropriate cloud solutions, using logical and simple techniques.

In this paper, comparing and selecting the most appropriate cloud solutions to manage big data projects is performed according to identified criteria provided by the Affinity Diagram as the first step of our proposed methodology. The decision making committee share information, knowledge and judgments until a mutual consensus is reached on the influential criteria. In the second step, fuzzy AHP process is employed to decompose the decision-making problem into its constituent parts and construct hierarchies of the influential criteria in order to generate the criteria and sub-criteria weight. In the last step, we use TOPSIS process to build an overall performance score in order to measure the performance of each alternative, and then, conduct a sensitivity analysis to estimate the decision maker's risks and identify the influence of criteria weights on the decision making process. The application of our proposed integrated approach allows the policy makers of a company not only to determine the significant criteria, but also to compare, evaluate and select the proposed alternatives appropriately.

For further studies, the comparison of this methodology with different multi-criteria decision making techniques such as PROMETHEE, ELECTRE and VIKOR can be used and the results of its application in different areas can be presented, especially in the financial field where multiple conflicting criteria are considered.

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