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Article

An Integrated Framework for Cloud Service Selection Based on BOM and TOPSIS

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Abstract: Many businesses have experienced difficulties in selecting a cloud service provider (CSP) due to the rapid advancement of cloud computing services and the proliferation of CSPs. Many independent criteria should be considered when evaluating the services provided by different CSPs. It is a case of multi-criteria decision-making (MCDM). This paper presents an integrated MCDM cloud service selection framework for determining the most appropriate service provider based on the best only method (BOM) and technique for order of preference by similarity to ideal solution (TOPSIS). To obtain the weights of criteria and the relative importance of CSPs based on each criterion, BOM performs pairwise comparisons of criteria and also for alternatives on each criterion, and TOPSIS uses these weights to rank cloud alternatives. An evaluation and validation of the proposed framework have been carried out through a use-case model to prove its efficiency and accuracy. Moreover, the developed framework was compared with the analytical hierarchical process (AHP), a popular MCDM approach, based on two perspectives: efficiency and consistency. According to the research results, the proposed framework only requires 25% of the comparisons needed for the AHP approach. Furthermore, the proposed framework has a CR of 0%, whereas AHP has 38%. Thus, the proposed framework performs better than AHP when it comes to computation complexity and consistency, implying that it is more efficient and trustworthy.

Keywords: Cloud computing (CC); multiple-criteria decision-making (MCDM); cloud service providers (CSPs); analytical hierarchical process (AHP); the best only method (BOM); technique for order of preference by similarity to ideal solution (TOPSIS)

1 Introduction

Cloud computing [1] is critical for start-ups and small businesses that want to launch a low-cost business model. The concept describes a novel utility computing type for providing customers with storage, computing resources, platforms, software, etc., on a pay-per-use basis through the Internet

[2]. Its primary goal is to deliver services ranging from computing resources to applications through the Internet that is accessible at any time and from any location. The advantages of cloud hosting, such as scalability, flexibility, and dependability, have driven businesses to rely on it for their enterprises, resulting in an exponential increase in cloud customers [3]. Cloud computing consists of three parts: (i) cloud service providers (CSPs), (ii) data owners, and (iii) users. CSP acts as the central authority in a cloud environment by controlling all operations. The cloud server holds data stored by data owners, while users can access this data and services [4,5]. Numerous CSPs have made it challenging for customers to the most appropriate CSP that meets their functional and non-functional needs [6]. CSPs should be assessed against a set of quality-of-service (QoS) metrics, along with a method for ranking them based on those metrics to select the best provider [7]. Consequently, the world's largest organizations have formed the cloud services measurement initiative consortium (CSMIC) [8], which aims to standardize the QoS metrics used to evaluate the quality of service offered by CSPs. The CSMIC developed a model known as the service measurement index (SMI), which includes seven primary criteria such as usability and security. Each criterion was subdivided into several sub-criteria. Cloud customers use these criteria to evaluate different CSPs. Thus, choosing a cloud service provider requires multiple-criteria decision-making (MCDM). The goal of MCDM is to evaluate and rank alternatives (CSPs) based on the selected criteria [9]. Cloud customers will find it incredibly challenging to select the most appropriate CSP based on their preferences due to many existing CSPs and the wide range of evaluating criteria. The selection of cloud services has been the subject of several recent studies [10–12]. Even though these studies have been validated thoroughly, they still have flaws, including low comparison consistency and increased processing complexity, which remain major issues in the selection of cloud services. A consistent, robust, and computationally efficient MCDM framework is presented in this paper. In order to rank the available CSPs, the proposed framework combines the TOPSIS technique and our developed BOM method. The BOM is used to determine the relative weights of alternatives and the weights of criteria. These weights are used by TOPSIS to rank cloud alternatives. Fig. 1 shows the structure of the proposed integrated framework and its interaction with cloud customers and decision-makers.

The proposed integrated framework was validated using a use-case model, demonstrating its efficiency and consistency. In addition, it was compared with the AHP method. Results clearly demonstrate that the proposed framework is robust, efficient, and entirely consistent compared to the AHP method.

The rest of the paper is organized as follows: AHP and TOPSIS methods are discussed in Section 2, and related work is presented in Section 3. A detailed description of the proposed integrated framework is provided in Section 4. In Section 5, experimental results using a use-case model are presented. Section 6 provides an evaluation of our proposed framework and compares it to AHP. Section 7 concludes the paper.

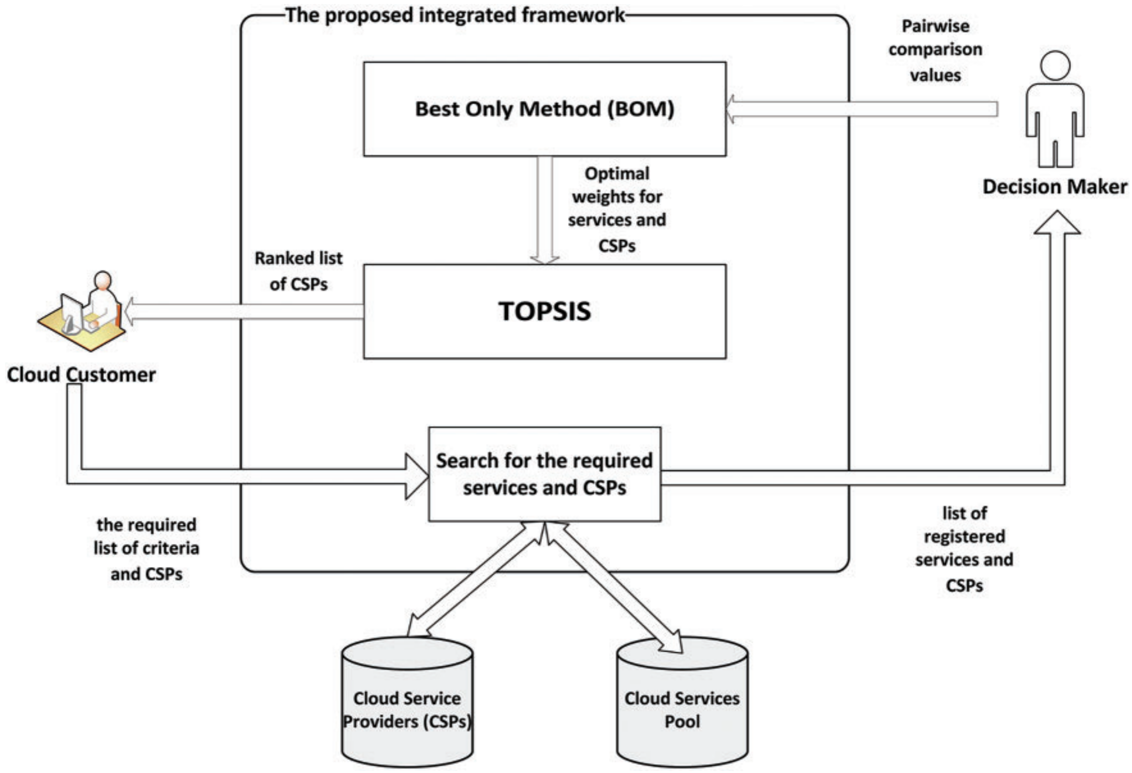

Figure 1: The proposed framework

2 Background

2.1 AHP

For solving complex decisions, Saaty's AHP is one of the most commonly used methods [13–15]. Specifically, it identifies the goals, the criteria, the subcriteria, and the alternatives for solving a problem. In choosing the best alternative, the AHP allows both objective and subjective factors to be considered, mainly when the subjective preferences of decision-makers play a significant role [16,17]. Three components underlie the AHP method: decomposition, comparative judgments, and prioritization. Based on the principle of decomposition, a problem may be viewed as a hierarchical system. The first level represents the overall objective, while the subsequent levels represent the criteria and alternatives. A comparative judgment is made by comparing elements at each level relative to one element at the next upper level, beginning at the first level of the hierarchy and proceeding downward. A set of preference matrices are produced due to comparing elements at each level [18]. Saaty's scale of relative preference provides the decision-maker with the basis for their judgments [19].

Let us suppose that we have n criteria $c_1, c_2, \cdots, c_n$. Matrix "A" represents the relative preference of the criteria based on $n \times n$ pairwise comparisons as in Eq. (1).

$$A = \begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \tag{1}$$

a_{ij} indicates the relative preference (importance) of criterion a_i over a_j, and $i, j = 1, 2, 3, \ldots, n$.

where:

$a_{ij} = 1$, indicates that criteria i and j are equally important.

$a_{ij} > 1$, indicates that the importance of criterion i is more significant than criterion j.

$a_{ij} < 1$, indicates that the importance of criterion i is less than criterion j.

The decision-maker is presumed to be consistent in his/her judgments concerning any pair of alternatives. Furthermore, when compared with themselves, all alternatives are ranked equally. Thus, we have $a_{ij} = 1/a_{ji}$ (the property of reciprocal) and $a_{ii} = 1$ [17]. Thus, matrix "A" may only need $n \times (n-1)/2$ comparisons.

As demonstrated in [13], if matrix "A" is perfectly consistent, Eq. (1) can be rewritten as follows:

$$A = \begin{pmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \cdots & \frac{w_2}{w_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & \frac{w_n}{w_n} \end{pmatrix} \tag{2}$$

where $w_1, w_2, \cdots, w_n$ represent the corresponding weight of each criterion $c_1, c_2, \cdots, c_n$, respectively. Each criterion's weight value may be calculated using Eq. (3) as follows:

$$\begin{pmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} = n \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} \tag{3}$$

Accordingly, n is referred to as the principal eigenvalue of matrix "A", and its eigenvector is $w = (w_1 w_2 \cdots w_n)^T$ [13].

When making real-world decisions, we are unable to specify the precise values of w_i/w_j; only estimated values may be stated. It is essential to consider the possible errors of judgment that a decision-maker might make when providing estimates of these values. The theory of eigenvalue states that a relatively minor alteration in a simple eigenvalue will lead to an eigenvalue issue as follows [13]:

$$Aw = \lambda_{max} w \tag{4}$$

$$w_1 + w_2 + \cdots + w_n = 1 \tag{5}$$

Here, matrix "A" is inconsistent although still reciprocal, and its principal eigenvalue is λ_{max}.

The weight values of the criteria may now be determined by solving Eqs. (4) and (5). After calculating the overall score value for each alternative, the next step is to determine the ranking of these alternatives according to this score. Based on the following formula on (6), final alternative scores were obtained:

$$R_i = \sum_{j=1}^{n} w_j V_{ij} \tag{6}$$

where R_i represents the weight of alternative i, w_j represents the weight of criterion j, V_{ij} represents the weight of alternative i relative to criterion j , and n is the number of criteria.

The consistency index (CI) is calculated as the negative average of the other roots of the characteristic polynomial of matrix “A” using the following formula [13]:

$$CI = \frac{\lambda_{max} - n}{n - 1} \tag{7}$$

A random index (RI) is similar to CI, except it is calculated as an average over many matrices of the same order that are reciprocal and constructed with random entries. The RI values corresponding to each value of n are given in Tab. 1 [20].

Table 1: Values of RI

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

According to the AHP method, consistency ratio (CR), a measure of the reliability of an MCDM method’s output, can be computed as follows:

$$CR = \frac{CI}{RI} \tag{8}$$

According to [13], if the consistency ratio of matrix “A” is less than or equal to 10%, the estimate is considered valid. Otherwise, consistency should be improved. If CR = 0, then values in matrix “A” are entirely consistent, and the following property is met for all of its elements [21]:

$$a_{ik} \times a_{kj} = a_{ij} \forall i, k, j \tag{9}$$

Compared with other multi-criteria approaches, AHP provides flexibility, simplicity, and the capability to detect inconsistencies. However, the disadvantage of AHP is that it requires a substantial number of pairwise comparisons equal to $(n(n-1)/2)$, which dramatically leads to complex computation [22]. Furthermore, there will likely be inconsistencies in pairwise comparisons, which often occur in practice [23].

2.2 TOPSIS

TOPSIS [24] is commonly regarded as one of the popular techniques used to solve MCDM problems. A basic idea of TOPSIS is that the optimal solution should be at the shortest Euclidian distance from the ideal positive solution. At the same time, it needs to be at the longest Euclidian distance from the ideal negative solution [25]. Accordingly, the best alternative is determined based on the Euclidian distance between each alternative and the ideal and the worst alternatives. The TOPSIS steps are outlined below.

Step 1: Construct the decision matrix “D” of size $m \times n$ where m and n are the numbers of alternatives and criteria, respectively. It is represented in Eq. (10).

$$D = \begin{pmatrix} d_{11} & d_{12} & \cdots & d_{1n} \\ d_{21} & d_{22} & \cdots & d_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d_{m1} & d_{m2} & \cdots & d_{mn} \end{pmatrix} \tag{10}$$

where d_{ij} is the weight of alternative i relative to criterion j.

Step 2: As each criterion is of a different type and thus has a different scale, calculate the normalized decision matrix "K" using Eq. (11) as shown below.

$$k_{ij} = \frac{d_{ij}}{\sqrt{\sum_{i=1}^{m} d_{ij}^{2}}}, \qquad i = 1, 2, 3, \ldots, m \qquad \text{and } j = 1, 2, 3, \ldots, n. \tag{11}$$

where k_{ij} is the normalized weight of alternative i relative to criterion j.

Step 3: Calculate the weighted matrix "H" based on Eq. (12) by multiplying the $w_j$values of the criteria by the corresponding normalized decision matrix elements k_{ij}.

$$h_{ij} = w_j * k_{ij} \tag{12}$$

where $i = 1, 2, 3, \ldots, m$ and $j = 1, 2, 3, \ldots, n$.

Step 4: Utilize the following equations to determine the positive ideal solution (PIS) and the negative ideal solution (NIS):

for beneficial criterion:

$$x_j^+ = max\left(h_{1j}, h_{2j}, \ldots., h_{mj}\right) \tag{13}$$

$$x_j^- = min\left(h_{1j}, h_{2j}, \ldots., h_{mj}\right) \tag{14}$$

and for non-beneficial criterion:

$$x_j^+ = min\left(h_{1j}, h_{2j}, \ldots., h_{mj}\right) \tag{15}$$

$$x_j^- = max\left(h_{1j}, h_{2j}, \ldots., h_{mj}\right) \tag{16}$$

Then:

$$PIS = \left\{x_1^+, x_2^+, \ldots, x_n^+\right\} \tag{17}$$

$$NIS = \left\{x_1^-, x_2^-, \ldots, x_n^-\right\} \tag{18}$$

Step 5: For each alternative, calculate the Euclidian distance E_i^+ and E_i^- using Eqs. (19)–(20).

$$E_i^+ = \sqrt{\sum_{j=1}^{n} \left(h_{ij} - x_j^+\right)^2} \tag{19}$$

$$E_i^- = \sqrt{\sum_{j=1}^{n} \left(h_{ij} - x_j^-\right)^2} \tag{20}$$

Step 6: Calculate the closeness value for each alternative (CV_i) using Eq. (21):

$$CV_i = \frac{E_i^-}{E_i^- + E_i^+} \tag{21}$$

Step 7: Rank the alternatives according to the closeness value. The best alternative is the one with the highest closeness value, which will be the first in the ranked list.

3 Related Work

A significant challenge associated with cloud computing has been selecting cloud services due to the large number of providers who offer similar services. For selecting cloud services, MCDM-based methods are the most straightforward and effective. In the literature, there are various MCDM-based cloud service selection frameworks. TOPSIS [25], AHP [26], ANP [27], MAUT [28], ELECTRE [29], SAW [30], and rank voting method [31] are the most common MCDM approaches for cloud service selection in the literature. Kumar et al. [25] developed a cloud service selection framework based on AHP and TOPSIS. They adopted a real-time dataset from CloudHarmony and made extensive sensitivity analyses to validate the model's efficacy. They conclude that the proposed model is effective when compared to other MCDM techniques. Garg et al. [26] created an AHP-based framework to evaluate cloud services based on various applications depending on QoS requirements. Such a framework can create healthy competition among Cloud providers to satisfy their Service Level Agreement (SLA) and improve their QoS. Tripathi et al. [27] incorporated the analytic network process (ANP) into the ranking component of the SMI framework. The interactions among the criteria in this method are used to rank cloud services. The proposed model's limitation is the number of selection criteria; if this number grows too large, it becomes difficult to keep track of all the interactions between them. Dyer [28] presents a summary of multiattribute utility theory and discusses the problem of multiattribute decisions. Dyer explores the use of multiattribute preference functions under uncertain and risky conditions to decompose them into additive and multiplicative forms. Various forms of multi-attribute preference functions are studied in relation to one another. The relationships between these various types of multi-attribute preference functions are investigated. Govindan et al. [29] thoroughly reviewed English scholarly articles on ELECTRE and ELECTRE-based approaches. This comprises application areas, method modifications, comparisons with other methods, and general research of the ELECTRE methods. The review includes 686 publications in all. Afshari et al. [30] presented an MCDM methodology for Personnel selection. It considers a real application of personnel selection with using the opinion of an expert by one of the decision-making models; it is called the SAW method. The limitation is that it ignores the fuzziness of the executive's judgment during the decision-making process. Baranwal et al. [31] identified several new QoS measures and described them to allow both the user and the provider to quantify their expectations and offers. They also proposed a dynamic and adaptable methodology that uses a form of the ranked voting method to analyze customers' needs and recommend the best cloud service provider. Case studies validate the suggested model's validity and effectiveness. Recent studies have used AHP to evaluate a variety of SaaS services [32,33], IaaS services [34,35], and general cloud services [36,37]. Saaty's basic 1-9 scale is commonly used to aid users in comparing and evaluating cloud service alternatives. The SMICLOUD framework was developed by Garg et al. [26] to compare and rank three IaaS cloud services using the SMI criteria [38]. According to this paper, the Cloud Service Measurement Initiative Consortium (CSMIC) has determined a set of metrics for measuring the QoS criteria, using which several CSPs are compared. Based on user preferences values, AHP is utilized to compute the weights for criteria, and then these weights are used to compare the three IaaS cloud services. CSPs were only selected based on the quantitative CSMIC criteria without recognizing the non-quantifiable QoS trustworthiness. Godse et al. [39] developed an AHP methodology to rank SaaS services, considering functionality, architecture, usability, vendor reputation, and pricing. Despite the usefulness of AHP, it fails to account for uncertainty in decisions when determining pairwise comparisons. A fuzzy AHP was developed to handle this issue, allowing decision-makers to use fuzzy ranking instead of precise ranking [40]. TOPSIS was used to rank alternatives according to the weights of criteria and alternatives determined by pairwise comparisons applied by AHP. They used the proposed method to assess the trustworthiness of 15 CSPs from several perspectives based on 9 QoS criteria (cost, speed, storage capacity, availability, response time, features, technical support, and ease of use). As a result of our analysis of these papers, we discovered that CSPs were evaluated based on several criteria, which led to more complex pairwise comparisons. Furthermore, most of these criteria are qualitative, resulting in inconsistent results in comparisons and, therefore, less reliable conclusions. This paper proposes a cloud service selection framework based on integrating BOM and TOPSIS methods for selecting the best CSP. In terms of computational complexity and consistency, the proposed framework outperformed AHP, making it more computationally efficient and perfectly consistent.

4 The Proposed Approach

This paper presents an integrated MCDM framework for selecting cloud computing services. The proposed framework incorporates the BOM method, which is used to calculate criteria weights and the relative weights of alternatives relative to each criterion, and TOPSIS, which uses these weights to produce the ranking for cloud alternatives (CSPs). Using the BOM approach, the decision-maker only determines the best criterion before evaluating that criterion against other criteria through pairwise comparisons. By doing so, all of the matrix's elements meet the property in (9), and all of its judgments are perfectly consistent. Fig. 2 depicts a flow chart summarizing the steps of the integrated framework.

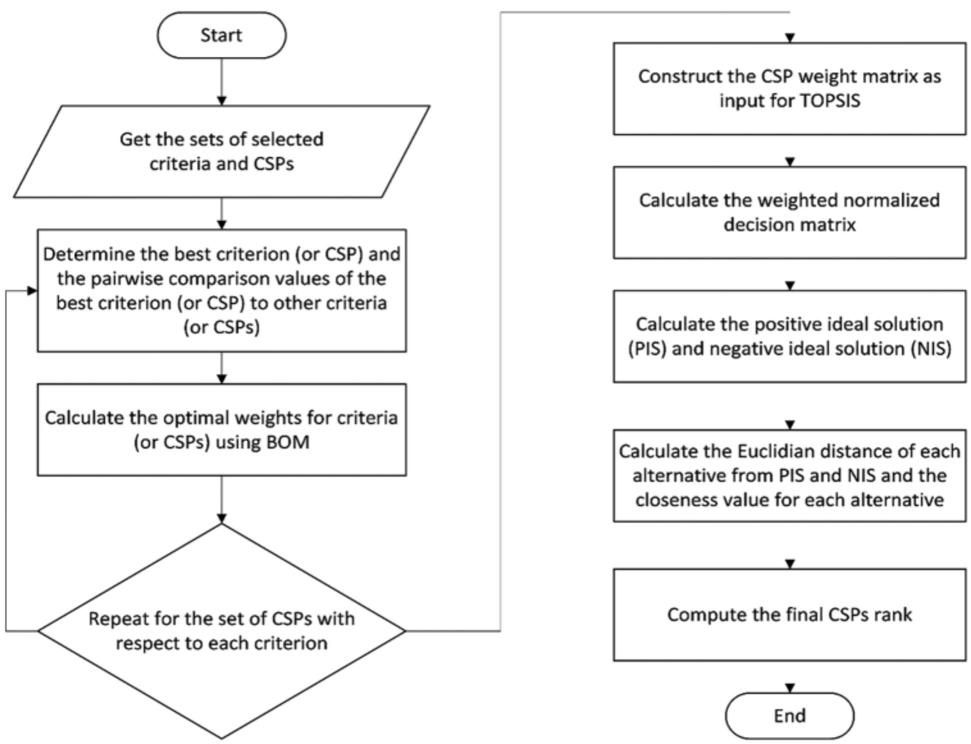

Figure 2: A flowchart showing the stages of the proposed framework

Step 1: (*Identify criteria that meet the business needs*): Assume that the set of criteria considered is $C = \{c_1, c_2, \cdots, c_n\}$. The number n represents the number of criteria.

Step 2: (*Identify the appropriate set of CSPs*): Assume that the set of CSPs considered is $SP = \{sp_1, sp_2, \cdots, sp_m\}$. The number m represents the number of CSPs.

Step 3: (*Identify the best criterion in the set of criteria*): Assume that the best criterion selected by the decision-maker is C_B where $C_B \in C$.

Step 4: (*Estimate the values of the pairwise comparison of the best criterion to the others*): Assume that the vector Cri_B represents the comparison values of the best criterion with the remaining criteria in C.

Step 5: (*Calculate the appropriate weights for each criterion*): Assume that C_W is the vector of size n that contains the weight values of *each criterion in* C. Obtaining the weight values requires solving the following problem:

$$\frac{w_B}{w_j} = a_{Bj} \; for \; all \; j \neq B \; and \; a_{Bj} \in Cri_B, j = 1, 2, 3, \ldots, n. \tag{22}$$

$$\sum_{j=1}^{n} w_j = 1 \tag{23}$$

Step 6: (*Determine the first criterion*): Suppose that the first criterion is c_1 where $c_1 \in C$.

Step 7: (*Select the best CSP relative to* c_1): Suppose the best CSP is SP_B the $SP_B \in SP$.

Step 8: (*Set the values of pairwise comparisons of the best CSP relative to* c_1): Assume that the vector CSP_B represents the pairwise comparison values of the best CSP to other providers in the set SP $w.r.t.$ c_1.

Step 9: (*Calculate the weight values of the CSPs* $w.r.t.$ c_1): To obtain the weight values of the CSPs, the following problem should be solved:

$$\frac{w_B}{w_i} = a_{Bi} \; for \; alli \neq B \; and \; a_{Bi} \in CSP_B, i = 1, 2, 3, \ldots, m. \tag{24}$$

$$\sum_{i=1}^{m} w_i = 1 \tag{25}$$

Step 10: (*Calculate the weights of CSPs concerning all other remaining criteria*): For all remaining criteria, repeat steps 7 through 9.

Step 11: (*Develop the matrix of CSP weights*): The matrix SP_W of size $m \times n$ represents the CSP weights. In this matrix, each column represents the weight values of the CSPs based on the criterion that corresponds to that column. This matrix represents the normalized decision matrix used by TOPSIS.

Step 12: (*Compute the weighted normalized decision matrix* H): H is calculated using Eq. (12) by multiplying the weight values of the criteria C_W_j by the corresponding columns in the normalized decision matrix (SP_W).

Step 13: (*Calculate the positive ideal solution* (PIS) *and negative ideal solution* (NIS)): For every criterion c_j, find the positive ideal solution x_j^+ and the negative ideal solution x_j^-, where:

$$x_j^+ = max\left(h_{1j}, h_{2j}, \ldots., h_{mj}\right) \tag{26}$$

$$x_j^- = min\left(h_{1j}, h_{2j}, \ldots., h_{mj}\right) \tag{27}$$

Then, compute the PIS and NIS values using Eqs. (17) and (18).

Step 14: (*Calculate the Euclidian distance* E_i^+ *and* E_i^- *of each alternative from PIS and NIS*): The Euclidian distance $\mathrm{E_i^+}$ and $\mathrm{E_i^-}$ for each criterion is calculated using Eqs. (19) and (20), respectively.

Step 15: (*Calculate the closeness value for each alternative* (CV_i)): The closeness value for each alternative CV_i is calculated using Eq. (21).

Step 16: (*Rank the alternatives in descending order of the closeness value*). The best alternative is the one with the highest closeness value.

5 Experimental Results

A use-case model was employed to analyze and validate the proposed framework, which proved its validity and efficacy.

Step 1. (*Identify criteria that meet the business needs*): Nine criteria were selected based on the SMI model, where $C = \{c_1, c_2, c_3, c_4, c_5, c_6, c_7, c_8, c_9\}$ and n = 9. Tab. 2 shows the set of selected criteria.

Table 2: The selected criteria in this paper

Symbol	Criterion
c_1	Adaptability
c_2	Scalability
c_3	Sustainability
c_4	Cost
c_5	Reliability
c_6	Accessibility
c_7	Accuracy
c_8	Security Management
c_9	Data Integrity

Step 2. (*Identify the appropriate set of CSPs*): For our use-case model, eight hypothetical CSPs were chosen, where $SP = \{sp_1, sp_2, sp_3, sp_4, sp_5, sp_6, sp_7, sp_8\}$ and m = 8.

Step 3. (*Identify the best criterion in the set of criteria*): Assume that the best criterion chosen by the decision-maker is the *cost*. So, $C_B = C_4$.

Step 4. (*Estimate the values of the pairwise comparison of the best criterion to the others*): It is the responsibility of the decision-maker to determine the pairwise comparison values between each of the criteria in the set and the selected best criterion ($C_B - to - others$), shown in Tab. 3.

Table 3: The values of ($C_B - to - others$) comparisons

$\boldsymbol{C_B - to - others}$	Comparison value
$c_4 - to - c_1$	9
$c_4 - to - c_2$	3
$c_4 - to - c_3$	5
$c_4 - to - c_4$	1
$c_4 - to - c_5$	4
$c_4 - to - c_6$	7

(Continued)

Table 3: Continued

$C_B - to - others$	Comparison value
$c_4 - to - c_7$	6
$c_4 - to - c_8$	2
$c_4 - to - c_9$	8

Step 5. (*Calculate the appropriate weights for each criterion*). Tab. 4 shows the weight values of the set of criteria, which are computed using Eqs. (22) and (23), respectively.

Table 4: The weight values of the set of criteria

Criterion	Weight
c_1	0.0393
c_2	0.1178
c_3	0.0707
c_4	0.3535
c_5	0.0884
c_6	0.0505
c_7	0.0589
c_8	0.1767
c_9	0.0442

The values from Tab. 4 are stored in the vector (C_W) as follows:

$$C\_W = \begin{pmatrix} 0.0393 & 0.1178 & 0.0707 & 0.3535 & 0.0884 & 0.0505 & 0.0589 & 0.1767 & 0.0442 \end{pmatrix}$$

Step 6. (*Determine the first criterion*).

Step 7. (*Select the best CSPrelative to c_1*): Assume that SP_5 was chosen by the decision-maker.

Step 8. (*Set the values of pairwise comparisons of the best CSP relative to c_1*): The comparison values of SP_5 *relative to* c_1 ($SP_5 - to - others$) is stated by the decision-maker *and shown in* Tab. 5.

Table 5: The values of ($SP_5 - to - others$) comparisons $w.r.t.$ c_1

$SP_5 - to - others$	Comparison value
$SP_5 - to - SP_1$	3
$SP_5 - to - SP_2$	4
$SP_5 - to - SP_3$	7
$SP_5 - to - SP_4$	2
$SP_5 - to - SP_5$	1
$SP_5 - to - SP_6$	8

(Continued)

Table 5: Continued

$SP_5 - to - others$	Comparison value
$SP_5 - to - SP_7$	9
$SP_5 - to - SP_8$	6

Step 9. (*Calculate the weight values of the CSPs w.r.t.* c_1):

Tab. 6 shows the weight values of the CSPs $w.r.t.$ c_1 computed using Eqs. (24) and (25).

Table 6: The weight values of the CSPs w.r.t. c_1

CSP	Weight
SP_1	0.1268
SP_2	0.0951
SP_3	0.0543
SP_4	0.1902
SP_5	0.3804
SP_6	0.0475
SP_7	0.0423
SP_8	0.0634

Step 10. (*Calculate the weights of CSPs concerning all other remaining criteria*): For all remaining criteria, repeat steps 7 through 9. In Tab. 7, the The ($SP_B - to - others$) comparison values $w.r.t.$ each criterion are presented in tabular format. In our use-case model, there are nine criteria (columns) and eight CSPs (rows). The decision-maker determines which CSP is the best for each of the criteria and estimates the values of pairwise comparisons of each CSP relative to the others. In Tab. 7, Each shaded cell represents the optimal CSP based on the criterion.

Table 7: The ($SP_B - to - others$) values for all criteria

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9
SP_1	3	**1**	4	9	8	5	6	9	4
SP_2	4	5	3	8	7	**1**	4	2	5
SP_3	7	8	4	6	5	7	**1**	5	3
SP_4	2	2	6	4	4	6	5	8	**1**
SP_5	**1**	3	7	2	**1**	9	8	6	2
SP_6	8	7	5	**1**	2	4	7	4	6
SP_7	9	8	4	3	2	8	9	**1**	7
SP_8	6	9	**1**	7	6	2	2	3	8

Step 11. (*Develop the matrix of CSP weights*): In Tab. 8, each column contains the CSPs weights for each criterion.

Table 8: The CSPs weight matrix

	c_1	c_2	c_3	c_4	c_5	c_6	c_7	c_8	c_9
SP_1	0.1268	0.3941	0.0964	0.0423	0.0433	0.0801	0.0668	0.0414	0.0920
SP_2	0.0951	0.0788	0.1286	0.0475	0.0495	0.4007	0.1002	0.1861	0.0736
SP_3	0.0543	0.0493	0.0964	0.0634	0.0693	0.0572	0.4007	0.0745	0.1226
SP_4	0.1902	0.1971	0.0643	0.0951	0.0867	0.0668	0.0801	0.0465	0.3679
SP_5	0.3804	0.1314	0.0551	0.1902	0.3467	0.0445	0.0501	0.0620	0.1840
SP_6	0.0475	0.0563	0.0771	0.3804	0.1733	0.1002	0.0572	0.0931	0.0613
SP_7	0.0423	0.0493	0.0964	0.1268	0.1733	0.0501	0.0445	0.3723	0.0526
SP_8	0.0634	0.0438	0.3857	0.0543	0.0578	0.2003	0.2003	0.1241	0.0460

The values from Tab. 8 are represented in the normalized decision matrix (SP_W) as follows:

$$SP\_W = \begin{pmatrix} 0.1268 & 0.3941 & 0.0964 & 0.0423 & 0.0433 & 0.0801 & 0.0668 & 0.0414 & 0.0920 \\ 0.0951 & 0.0788 & 0.1286 & 0.0475 & 0.0495 & 0.4007 & 0.1002 & 0.1861 & 0.0736 \\ 0.0543 & 0.0493 & 0.0964 & 0.0634 & 0.0693 & 0.0572 & 0.4007 & 0.0745 & 0.1226 \\ 0.1902 & 0.1971 & 0.0643 & 0.0951 & 0.0867 & 0.0668 & 0.0801 & 0.0465 & 0.3679 \\ 0.3804 & 0.1314 & 0.0551 & 0.1902 & 0.3467 & 0.0445 & 0.0501 & 0.0620 & 0.1840 \\ 0.0475 & 0.0563 & 0.0771 & 0.3804 & 0.1733 & 0.1002 & 0.0572 & 0.0931 & 0.0613 \\ 0.0423 & 0.0493 & 0.0964 & 0.1268 & 0.1733 & 0.0501 & 0.0445 & 0.3723 & 0.0526 \\ 0.0634 & 0.0438 & 0.3857 & 0.0543 & 0.0578 & 0.2003 & 0.2003 & 0.1241 & 0.0460 \end{pmatrix}$$

Step 12: (*Compute the weighted normalized decision matrix H*): H is calculated using Eq. (12) by multiplying the weight values of the criteria C_W_j by the corresponding columns in the normalized decision matrix (SP_W).

$$H = \begin{pmatrix} 0.0050 & 0.464 & 0.0068 & 0.0149 & 0.0038 & 0.0040 & 0.0039 & 0.0073 & 0.0041 \\ 0.0037 & 0.0093 & 0.0091 & 0.0168 & 0.0044 & 0.0202 & 0.0059 & 0.0329 & 0.0033 \\ 0.0021 & 0.0058 & 0.0068 & 0.0224 & 0.0061 & 0.0029 & 0.0236 & 0.0132 & 0.0054 \\ 0.0075 & 0.0232 & 0.0045 & 0.0336 & 0.0077 & 0.0034 & 0.0047 & 0.0082 & 0.0163 \\ 0.0149 & 0.0155 & 0.0039 & 0.0672 & 0.0306 & 0.0022 & 0.0030 & 0.0110 & 0.0081 \\ 0.0019 & 0.0066 & 0.0055 & 0.1345 & 0.0153 & 0.0051 & 0.0034 & 0.0164 & 0.0027 \\ 0.0017 & 0.0058 & 0.0068 & 0.0448 & 0.0153 & 0.0025 & 0.0026 & 0.0658 & 0.0023 \\ 0.0025 & 0.0052 & 0.0273 & 0.0192 & 0.0051 & 0.0101 & 0.0118 & 0.0219 & 0.0020 \end{pmatrix}$$

Step 13: (*Calculate the positive ideal solution (PIS) and negative ideal solution (NIS)*): The vectors PIS and MIS are calculated using equations 13 through 18, and the results are as follow:

$$PIS = \begin{pmatrix} 0.0149 & 0.0464 & 0.0273 & 0.1345 & 0.0306 & 0.0202 & 0.0236 & 0.0658 & 0.0163 \end{pmatrix}$$

$$NIS = \begin{pmatrix} 0.0017 & 0.0052 & 0.0039 & 0.0149 & 0.0038 & 0.0022 & 0.0026 & 0.0073 & 0.0020 \end{pmatrix}$$

Step 14: (*Calculate the Euclidian distance E_i^+ and E_i^- of each alternative from PIS and NIS*): The Euclidian distance E_i^+ and E_i^- of each criterion is calculated and shown in Tab. 9.

Step 15: (*Calculate the closeness value for each alternative (CV_i)*): The closeness value for each alternative CV_i is calculated and shown in Tab. 9.

Step 16: (*Rank the alternatives in descending order of the closeness value*). Tab. 9 shows the final CSP ranking.

Table 9: Values of Euclidian distances and final ranked list of CSPs

	E_i^+	E_i^-	CV_i	Ranking
SP_1	0.1405	0.0416	0.2286	4
SP_2	0.1339	0.0323	0.1943	6
SP_3	0.1363	0.0236	0.1476	8
SP_4	0.1256	0.0305	0.1956	5
SP_5	0.0992	0.0615	0.3827	3
SP_6	0.0757	0.1205	0.6142	**1**
SP_7	0.1071	0.0667	0.3840	2
SP_8	0.1348	0.0304	0.1843	7

6 Evaluation

Several measures of the viability of the proposed framework have been considered: computing efficiency (In terms of the number of comparisons made between all pairs) and consistency ratio (CR). Validation was achieved by comparing it with the AHP technique. The exact configuration was used in our comparison experiments for the developed framework and the AHP technique. The AHP computations were carried out using the method presented in [41].

6.1 Computation Efficiency

We calculated the number of pairwise comparisons given by the decision-maker to assess the efficiency of the proposed framework. Nine criteria and eight CSPs were used in all of our experiments. In Tab. 10, we compare the number of comparisons in AHP with those in the developed framework. In contrast with AHP, our proposed framework does not require as many comparisons, thus making it more efficient. It is in part because the proposed framework uses a vector-based approach rather than a matrix-based approach such as AHP, which requires fewer comparisons. For AHP, $n \times (n-1)/2$ comparisons are needed, while for the developed framework, only $n-1$ comparisons are needed. Fig. 3 illustrates the computational complexity of AHP in contrast to the developed framework. Compared with AHP, the proposed framework requires fewer pairwise comparisons, which implies a reduction in computational effort.

Table 10: Comparisons between AHP and the proposed framework as measured by the number of pairwise comparisons

Pairwise Vector/Matrix	No. of Comparisons	
	AHP	The proposed framework
Criteria	36	8
CSPs-C1	28	7
CSPs-C2	28	7
CSPs-C3	28	7
CSPs-C4	28	7
CSPs-C5	28	7
CSPs-C6	28	7
CSPs-C7	28	7
CSPs-C8	28	7
CSPs-C9	28	7
Total	288	71

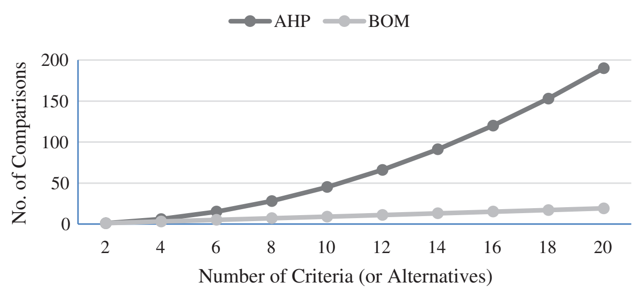

Figure 3: Computational complexity of AHP, BWM, and BOM

6.2 Consistency Ratio (CR)

The reliability of MCDM results is based on the value of the consistency ratio. In our experiment, the CR is calculated using the AHP technique and the proposed framework to evaluate consistency. Tab. 11 compares the CR results of the proposed framework and the AHP technique. For AHP, CR is calculated using Eq. (8). According to the AHP technique, if the comparisons have consistency ratio values greater than or equal to 0.1, they are considered inconsistent.

Based on the eigenvalue theory, if the value of $\lambda_{max} = n$, then the pairwise comparison matrix (or vector) is considered entirely consistent. This means that the developed framework is always entirely consistent (CR = 0). Therefore, it is a more reliable and consistent framework in comparison to AHP.

Table 11: Comparative analysis of the proposed framework to AHP based on consistency

Pairwise Matrix/Vector	Consistency Ratio (CR%)	
	AHP	The proposed framework
Criteria	30.20%	0.00%
CSPs-C1	33.25%	0.00%
CSPs-C2	28.31%	0.00%
CSPs-C3	34.57%	0.00%
CSPs-C4	41.03%	0.00%
CSPs-C5	60.92%	0.00%
CSPs-C6	29.87%	0.00%
CSPs-C7	52.01%	0.00%
CSPs-C8	37.37%	0.00%
CSPs-C9	31.68%	0.00%
Average	37.92%	0.00%

6.3 Analysis and Discussion

We have evaluated and ranked eight CSPs (m = 8) based on nine criteria (n = 9), driven by the decision-makers preferences. The proposed framework was compared to a well-known MCDM method, AHP, using the same configurations to validate the proposed framework's efficiency and consistency. AHP requires ten matrices: one of size $9x9$ determines the weight values of criteria, and nine other matrices of size $8x8$ determine the weight values of CSPs relative to each of the criteria. According to the AHP method, the decision-maker should estimate $9 \times (9-1)/2 + 9 \times 8 \times (8-1)/2 = 288$ comparisons. The proposed framework requires only ten vectors: one vector of size $1x9$ to calculate the weight values of criteria and nine vectors of size $1x8$ to calculate the weight values of CSPs w.r.t.each criterion. According to our developed framework, the decision-maker should estimate $(9-1) + 9 \times (8-1) = 71$ comparisons. Thus, the proposed framework only requires 25% of the comparisons required by the AHP approach. Moreover, the proposed framework is fully consistent since the decision-maker only uses the best criterion (or best CSP) to estimate the values of pairwise comparisons. According to the obtained results, the proposed framework has a CR of 0%, whereas AHP has a CR of 38%. As with AHP, one limitation of the proposed framework is that the accuracy of the decision depends on the estimations done by the decision-maker for the values of the pairwise comparisons of qualitative criteria.

7 Conclusion

This paper proposed an integrated MCDM framework to enable cloud service customers to select the most appropriate CSP by utilizing the BOM and the TOPSIS methods. A formal evaluation and verification of the proposed framework were conducted utilizing a use-case model to validate its effectiveness and consistency. A comparison was made between the proposed framework and AHP. In terms of computing complexity and consistency, our proposed framework performs superior to AHP. Similar to AHP, the proposed framework has the drawback that it relies on decision-makers' judgments of the pairwise comparison values for qualitative criteria to reach the final ranking list of CSPs. In the future, this work can be extended to include group decision-making.

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