Fuzzy Analytics Spectrum

Journal homepage: www.fas.journal-publishing.org
ISSN: XXXX-XXXX

Integrating Fuzzy SWARA and TOPSIS Methods for Cloud Service Selection

Petar Bosiljčić[1*]

[1] Department of Computing and Control Engineering, Faculty of Technical Sciences Novi Sad, University of Novi Sad, Novi Sad, Serbia

ARTICLE INFO

Article history:
Received 12 June 2026
Received in revised form 10 August 2026
Accepted 13 September 2026
Available online 21 September 2026

Keywords:
Cloud services; Fuzzy approach; Fuzzy SWARA; Fuzzy TOPSIS

ABSTRACT

This research employs a hybrid framework for cloud service selection that integrates multi-criteria decision-making methods with a fuzzy approach. Specifically, fuzzy SWARA (Step-wise Weight Assessment Ratio Analysis) and fuzzy TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) are applied. The fuzzy SWARA method is used to determine the weights of ten selected criteria based on expert assessments. The results obtained from 16 experts indicate that cost (C1) and security (C3) are the most important criteria for cloud service selection. The fuzzy TOPSIS method is used to rank six cloud services. Services A6 and A1 achieve the best results, making them the most suitable choices for companies in Serbia. Additional comparative and sensitivity analyses confirm these findings and demonstrate the need to balance cost, security, and performance when selecting cloud services. The contribution of this research lies in the application of a flexible decision-making model based on fuzzy SWARA and fuzzy TOPSIS. The model can also be applied to other decision-making problems, provided that appropriate adjustments are made to the criteria and alternatives.

1. Introduction

Cloud computing has revolutionized the way data is accessed, stored, and processed. It has shifted the paradigm from investing in physical infrastructure to renting computing resources, thereby enabling cost reductions and increased flexibility in data management [1]. The shift driven by the adoption of cloud computing is not merely technological but also strategic, as it transforms how data is accessed, stored, and processed, thereby directly impacting corporate competitiveness and enabling enhanced data security [2, 3].

The cloud services market is characterized by significant diversity and complexity regarding the selection of a suitable platform. Many companies offer a wide range of services, spanning from basic data storage to advanced AI-driven data management systems [4]. Consequently, cloud computing offerings vary widely in terms of pricing models, performance levels, security policies, geographic coverage, and other specifications, complicating the decision-making process [5]. Users

* *Corresponding author.*
E-mail address: petarbosiljcic@mail.ee

thus face the challenge of selecting a cloud service that meets their requirements while balancing various specifications [6, 7].

To address the challenge of selecting a cloud computing service provider, multi-criteria decision-making (MCDM) can be employed; this serves as a tool for resolving such selection problems by enabling decision-making in the presence of conflicting criteria [8]. In this context, MCDM methods are typically applied based on Quality of Service (QoS), taking into account a variety of criteria [9]. Traditional MCDM methods rely on pre-existing data regarding alternative specifications and require precise, fully defined inputs; however, such data is difficult to obtain when evaluating service quality. Consequently, decisions are often based on expert assessments, which inherently involve a degree of uncertainty and ambiguity [10]. To address this, a fuzzy approach is commonly employed, allowing for the use of imprecise information represented as linguistic ratings [11].

The motivation for this research stems from the specific nature of selecting cloud computing services. This decision-making process involves conflicting criteria, as improvements in specific service specifications typically lead to higher costs. Therefore, a compromise decision is required that takes into account established guidelines for cloud service selection. Furthermore, the process involves qualitative criteria for which exact data is unavailable; instead, values are derived through expert judgment [12]. Since this decision-making process entails a lack of complete information, experts must base their assessments on incomplete data, resulting in inherent uncertainty and ambiguity.

Given the complexity of selecting cloud services, this research pursues multiple objectives. Its primary goal is to develop a hybrid MCDM framework to support decision-making in the selection of cloud services. Based on this primary research objective, the following specific objectives are established:

- To identify and systematize evaluation criteria and cloud service alternatives
- To determine the importance of the criteria and rank the cloud services using a fuzzy approach
- To conduct an examination of the robustness of the proposed research model and the reliability of the research results.

To achieve these objectives, the following research questions must be addressed: First, what are the key criteria for evaluating cloud services? Second, how does the integration of fuzzy methods improve the selection of cloud services? Third, which cloud service delivers the best performance and is recommended for use? Fourth, how are comparative analysis and sensitivity analysis used to examine the robustness of the research model?

Overall, this research makes a threefold contribution. First, it offers a hybrid MCDM framework for cloud service selection using a fuzzy approach. Second, it provides a systematization of criteria for evaluating cloud services that can serve as a basis for future research. Third, through the validation of results, it offers practical guidelines for decision-makers regarding cloud service selection. These contributions are particularly significant given the increasing use of cloud services and the need for decision-making modeling that facilitates this choice.

2. Literature review

Selecting a cloud service is one of the challenges organizations face when digitizing their business operations. As noted by Gyani *et al.,* [5], this selection process involves multiple, often conflicting criteria; consequently, the decision-making problem falls within the domain of multi-criteria decision-making (MCDM). According to Hosseinzadeh *et al.,* [6], both quantitative and qualitative criteria must be considered during this selection, though precisely determining the data associated with these criteria can be difficult.

Various authors have proposed different sets of criteria for cloud service selection. In their research, Faiz and Daniel [9] utilized criteria such as cost, capacity, performance, security, and maintenance. Kahraman *et al.,* [11] employed criteria including speed, bandwidth, cost, security, and availability. Tiwari *et al.,* [13] used seven criteria to evaluate five cloud services. Liu *et al.,* [14] highlighted the difficulty of assigning values to cloud services based on these criteria, as they cannot always be precisely quantified. This issue is further complicated by the fact that each cloud service offers different pricing, performance levels, security standards, and geographic coverage; balancing these competing requirements adds complexity to the decision-making process [15]. For these reasons, applying an MCDM approach to cloud service selection serves as a valuable tool for reaching a final decision.

In studies regarding cloud service selection, Kumar *et al.,* [16] analyzed research published between 2012 and 2023 and confirmed that AHP (Analytic Hierarchy Process), TOPSIS, and VIKOR (ser. VIseKriterijumska Optimizacija I Kompromisno Resenje) are the most frequently used MCDM methods. On the other hand, Rahimi *et al.,* [7] classified cloud service selection approaches into three main groups: decision-making methods, metaheuristic methods, and fuzzy methods. MCDM methods have been used for cloud service selection, and an overview of several studies is presented in Table 1.

Table 1
Overview of research on the application of MCDM methods in cloud service selection

Author	Method	Brief contribution
Araujo *et al.,* [1]	TOPSIS	Ranking cloud systems based on reliability and cost.
Youssef [17]	BWM and TOPSIS	Determining the ranking of cloud service providers and comparing results with the AHP method.
Jatoth *et al.,* [2]	AHP and Grey TOPSIS	Using grey theory to handle incomplete data when selecting cloud services.
Tomar *et al.,* [18]	AHP, entropy and TOPSIS	Combining subjective and objective weights to rank cloud services.
Ghorui *et al.,* [8]	AHP and TOPSIS	Applying pentagonal intuitionistic fuzzy numbers to rank cloud services.
Monika and Sangwan [10]	AHP and TOPSIS	A framework for evaluating cloud services using interval-valued spherical fuzzy sets.
Thasni *et al.,* [19]	TOPSIS	Cloud service selection using interval-valued fuzzy logic.
Abdel-Basset *et al.,* [3]	AHP	A neutrosophic approach to assessing cloud service quality.
Mandal and Khan [20]	CoCoSo	A model based on cloud theory for handling uncertainty in cloud service assessments.
Liu *et al.,* [21]	Entropy and GRA-ELECTRE III	An approach for handling heterogeneous QoS attributes in cloud service selection.

This brief overview reveals that the AHP and TOPSIS methods are the most widely used, as demonstrated by Kumar *et al.,* [16] in their research. Consequently, the fuzzy TOPSIS method was selected for this study to rank cloud services. However, the fuzzy SWARA method will be used to determine the importance of the criteria. Unlike the AHP method, this approach does not require a large number of pairwise comparisons; SWARA enables more efficient weight determination through fewer comparisons.

3. Research methodology

This study combines various approaches to determine which of the observed cloud services yields the best indicators and can be considered the primary choice. To carry out this research, the methodology comprises four phases:

- Identification of criteria and alternatives,

- Data collection from experts,
- Application of the fuzzy SWARA and TOPSIS methods, and
- Conducting additional analyses.

3.1 Selection of criteria and alternatives

Based on a detailed literature review, ten key criteria for evaluating cloud services were identified. These criteria were selected to encompass technical, economic, and organizational aspects intended to assist decision-makers in the selection of cloud services. Table 2 provides an overview of the identified criteria, their descriptions, and the supporting references from previous studies.

Table 2
Criteria for evaluating cloud providers

ID	Criterion	Criterion Description	References
C1	Cost	Total costs of using cloud services, including expenses for storage, computing resources, data transfer, and additional services	[5], [9], [11]
C2	Performance	Performance speed, response time, and request processing latency	[6], [13], [14]
C3	Security	Data protection level, authentication mechanisms, encryption, security policies, and compliance with security standards	[5], [9], [11]
C4	Availability	Service uptime and access reliability	[6], [7], [16]
C5	Scalability	Ability to easily scale resources up or down according to user needs	[13], [14], [19]
C6	Reliability	System stability, failure frequency, and recovery time	[7], [11], [16]
C7	Support	Quality of technical support, availability, and response speed	[9], [19], [22]
C8	Flexibility	Ability to customize services to specific user needs and compatibility with existing systems	[5], [13], [14]
C9	Vendor reputation	Provider's market reputation, experience, and user base	[6], [7], [16]
C10	Compliance	Compliance with international standards and regulatory requirements	[9], [11], [19]

For the purposes of this study, six cloud services most widely used in Serbia were selected. These services differ from one another and cater to specific market segments. They have been anonymized to ensure the research focuses on the methodology rather than on specific commercial entities. The characteristics of these systems are as follows:

- Alternative A1 represents a major global cloud service with the broadest range of services; it operates in all regions and possesses the longest track record in the market. It is characterized by high costs but also by superior performance and reliability.
- Alternative A2 is a provider focused on integrating artificial intelligence and machine learning into its services, making it particularly suitable for organizations developing advanced analytics and AI applications.
- Alternative A3 specializes in the needs of small and medium-sized enterprises, offering simple packages at competitive prices with an emphasis on customer support and ease of use.
- Alternative A4 stands out for its advanced security standards, focusing on industries with strict regulatory requirements, such as banking, healthcare, and public administration.
- Alternative A5 offers the most affordable pricing for startups and educational institutions, featuring flexible billing models and free training.
- Alternative A6 ensures compliance with GDPR (General Data Protection Regulation) and prioritizes data sovereignty and transparency, offering a somewhat narrower range of services alongside high reliability.

3.2 Data Collection from Experts

The target group for this research consists of experts in the fields of information technology, cloud architecture, IT service management, and strategic management who have at least five years of experience working with cloud services and are based in Serbia. A purposive sampling method was used to select experts from various organizational levels and sectors, ensuring representativeness and diversity regarding cloud service selection. A total of 16 experts participated in this study. This number aligns with recommendations for MCDM studies employing a group-based approach, where the total number of experts typically ranges from 5 to 20 [12, 14]. Table 3 presents the demographic and professional characteristics of the experts involved in this study.

Table 3
Expert characteristics

Expert	Gender	Age (years)	Years of experience	Education	Position	Sector
E1	M	35-44	12	Ph.D	Cloud Architect	IT Consulting
E2	F	45-54	20	M.S.	IT Director	Finance
E3	M	25-34	6	M.S.	Cloud Engineer	Technology
E4	M	55+	28	Ph.D	Professor (Cloud Computing)	Academic
E5	F	35-44	10	M.S.	IT Service Manager	Healthcare
E6	M	25-34	5	M.S.	DevOps Engineer	E-commerce
E7	M	45-54	18	Ph.D	IT Strategist	Consulting
E8	F	35-44	9	M.S.	Security Architect	Public Sector
E9	M	35-44	11	M.S.	Cloud Manager	Education
E10	M	25-34	6	M.S.	System Administrator	Manufacturing
E11	F	45-54	16	Ph.D	Research Associate (IoT/Cloud)	Academic
E12	M	35-44	13	M.S.	IT Manager	Telecommunications
E13	F	25-34	5	M.S.	Cloud Consultant	Consulting
E14	M	55+	25	Ph.D	CTO	Finance
E15	M	35-44	8	M.S.	Solutions Architect	Technology
E16	F	45-54	15	M.S.	Digital Transformation Manager	Public Administration

Data collection was conducted in three steps. First, a questionnaire outlining the defined criteria and alternatives, along with detailed explanations of each criterion and descriptions and names of the alternatives, was distributed to the experts. Second, using a defined 7-point linguistic scale (Table 4), the experts assessed the importance of the criteria and evaluated how well the selected cloud services met those criteria. Third, the collected responses were processed and transformed into fuzzy numbers using a defined membership function; they were then aggregated using the fuzzy arithmetic mean to derive a single value representing all experts involved in the study, ensuring that each expert held equal weight in determining the ranking of the cloud services. All experts participated anonymously, and their responses were treated confidentially.

Table 4
Linguistic scales for evaluation

Linguistic ratings	Fuzzy number
Extremely poor (EP)	(0, 1, 2)
Very poor (VP)	(1, 2, 3)
Poor (PO)	(3, 4, 5)
Medium (ME)	(4, 5, 6)
Good (GO)	(6, 7, 8)
Very good (VG)	(7, 8, 9)
Extremely good (EG)	(8, 9, 10)

3.3 Application of Fuzzy SWARA and TOPSIS Methods

This study employs two fuzzy methods: SWARA, to determine criterion weights, and TOPSIS, to rank alternatives. The SWARA method was first introduced by Keršulienė *et al.,* [24] for determining the importance weights of criteria. This method involves ranking criteria assessments and establishing a rank order based on the interrelationships between the criteria. The steps of the SWARA method are as follows:

Step 1. Assessment of criteria using linguistic values.

Step 2. Transformation of linguistic values.

Step 3. Determination of the average score as a fuzzy number.

Step 4. Ranking of criteria based on average score values.

Step 5. Determination of criterion importance.

Step 6. Determination of relative importance.

$$k_j = \begin{cases} 1 \; if \; j = 1 \\ s_j + 1 \; if \; j > 1 \end{cases} \tag{1}$$

Step 7. Calculation of relative importance.

$$q_j = \begin{cases} 1 \; if \; j = 1 \\ \frac{q_{j-1}}{k_j} \; if \; j > 1 \end{cases} \tag{2}$$

Step 8. Determining the weight of the criteria.

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_k} \tag{3}$$

The TOPSIS method was developed by Hwang and Yoon [25] and is one of the most widely used MCDM methods in practice. Due to its widespread application, it is also employed in this study. The steps of the fuzzy TOPSIS method are:

Step 9. Evaluation of alternatives using linguistic values.

Step 10. Transformation of linguistic values and formation of the aggregated decision matrix.

Step 11. Normalization of the fuzzy aggregated decision matrix.

$$\tilde{n}_{ij} = \frac{x_{ij}^{l}}{max \; x_{ij}^{u}}, \frac{x_{ij}^{m}}{max \; x_{ij}^{u}}, \frac{x_{ij}^{u}}{max \; x_{ij}^{u}} \tag{4}$$

where $max \; x_{ij}^{u}$ is the maximum value of the fuzzy number for a particular criterion.

Step 12. Weighting the normalized decision matrix

$$\tilde{v}_{ij} = \tilde{n}_{ij} \cdot \widetilde{w}_{ij} \tag{5}$$

Step 13. Determination of ideal and anti-ideal solutions

$$A^{+} = \{\tilde{v}_1^{+}, \tilde{v}_2^{+}, \dots \tilde{v}_n^{+}\} = \{(\max x_i \tilde{v}_{ij} \; j \in J_1), (\min x_i \tilde{v}_{ij} \; j \in J_2)\} \tag{6}$$

$$A^{-} = \{\tilde{v}_1^{-}, \tilde{v}_2^{-}, \dots \tilde{v}_n^{-}\} = \{(\min x_i \tilde{v}_{ij} \; j \in J_1), (\max x_i \tilde{v}_{ij} \; j \in J_2)\} \tag{7}$$

Step 14. Calculation of deviations from ideal and anti-ideal solutions

$$S_i^{+} = \sqrt{\sum_{j=1}^{n} \left(\tilde{v}_{ij} - \tilde{v}_j^{+}\right)^2} \tag{8}$$

$$S_i^{-} = \sqrt{\sum_{j=1}^{n} \left(\tilde{v}_{ij} - \tilde{v}_j^{-}\right)^2} \tag{9}$$

Step 15. Calculation of the deviation from the ideal alternative

$$C_i = \frac{S_i^-}{S_i^- + S_i^+} \tag{10}$$

3.4 Additional analyses

A sensitivity analysis is conducted to examine the stability of alternative rankings when criterion weights change. This study employs a weight-variation scenario in which the weight of an individual criterion is adjusted across three levels—reduced by 20%, 50%, and 90% relative to its original weight—while the weights of the remaining criteria are increased proportionally. Since each of the 10 criteria is reduced three times, a total of 30 scenarios are generated for the sensitivity analysis. The ranking order for each scenario is then calculated using the fuzzy TOPSIS method. Subsequently, the resulting rankings are analyzed to determine which criteria are significant for specific alternatives. This process assesses the resilience of the alternatives to changes in criterion weights; high ranking stability indicates low sensitivity among the observed alternatives.

A comparative analysis is performed to validate the results obtained through the hybrid approach combining the fuzzy SWARA and TOPSIS methods. In this approach, weights derived via the fuzzy SWARA method are utilized, but the ranking is performed using other fuzzy methods on the same decision matrix (Table 5). This study involves ranking using five additional MCDM methods. The selected methods are as follows:

- SAW (Simple Additive Weighting): The simplest MCDM method, based on the additive aggregation of normalized values and criterion weights.
- MABAC (Multi-Attributive Border Approximation Area Comparison): A method that ranks alternatives based on their distance from the border approximation area.
- ARAS (Additive Ratio Assessment): A method that compares alternatives against an idealized reference alternative.
- CRADIS (Compromise Ranking of Alternatives from Distance to Ideal Solution): A modern method combining adapted steps from the TOPSIS, ARAS, and MARCOS methods, where ranking is based on the distance from ideal and anti-ideal solutions.
- MARCOS (Measurement of Alternatives and Ranking according to COmpromise Solution): A method that ranks alternatives relative to ideal and anti-ideal solutions and determines the degree of utility.

Table 5
Overview of methods used in the comparative analysis

Method	Type	Basic characteristic
SAW	Additive	Linear aggregation of normalized values
MABAC	Threshold	Distance from the approximation boundary area
ARAS	Relational	Relationship to the reference alternative
CRADIS	Compromise	Compromise ranking based on distance
MARCOS	Compromise	Relationship to the ideal and anti-ideal solutions

This approach provides a comprehensive and systematic framework for the selection of cloud services, featuring clearly defined steps and additional analyses that confirm the validity and stability of the obtained results.

4. Results

Linguistic ratings were used for the criteria and alternatives to derive the results of this study. These ratings were subsequently transformed, via a defined membership function, into fuzzy numbers, which were then utilized in the steps of the fuzzy method. Consequently, the process involves first determining the criteria weights and then ranking the alternatives. To determine the criteria weights, experts first assessed the individual importance of the criteria using linguistic values (Table 6).

Table 6
Assessment of criteria importance

Experts	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
E1	EG	EG	EG	EG	GO	EG	GO	GO	EG	EG
E2	VG	VG	EG	VG	GO	VG	VG	GO	VG	GO
E3	EG	GO	VG	GO	VG	GO	GO	ME	GO	GO
E4	EG	VG	EG	VG	GO	VG	GO	VG	VG	VG
E5	VG	GO	EG	GO	ME	VG	GO	GO	VG	VG
E6	EG	GO	VG	GO	GO	GO	VG	GO	GO	GO
E7	EG	VG	EG	VG	VG	VG	GO	GO	VG	VG
E8	VG	GO	EG	VG	GO	VG	GO	GO	VG	GO
E9	EG	VG	VG	VG	GO	VG	GO	GO	GO	VG
E10	GO	GO	GO	GO	GO	GO	ME	GO	GO	GO
E11	EG	VG	EG	VG	VG	VG	GO	GO	VG	VG
E12	EG	VG	VG	GO	GO	VG	GO	GO	VG	GO
E13	VG	ME	EG	ME	GO	ME	VG	GO	ME	GO
E14	EG	VG	EG	VG	VG	VG	GO	GO	VG	VG
E15	EG	VG	VG	VG	GO	VG	GO	ME	VG	VG
E16	GO	GO	GO	GO	GO	GO	GO	GO	GO	GO

Next, a transformation into fuzzy numbers was performed using a membership function. For instance, the value "Very good" is transformed into the fuzzy number (7, 8, 9), and the other linguistic values are transformed in the same manner (Table 4). Subsequently, the average values of these fuzzy numbers were calculated and used to determine weights via the fuzzy SWARA method. First, the criteria were ranked based on their average values, from highest to lowest. The next step involved establishing the differences between these criteria. The highest-ranked criterion is assigned a value of one, while the value of a specific criterion is subtracted from that of the higher-ranked one to calculate values for all criteria. For example, the greatest difference exists between criteria C6 and C3; this procedure will be demonstrated using that example.

$$s_{C6} = (7.44 - 6.63 = 0.81; 8.44 - 7.63 = 0.81; 9.44 - 8.63 = 0.81) \tag{11}$$

Due to the specificity of the defined fuzzy numbers, it happens that all values of the fuzzy numbers are the same. The next step is to determine the relative importance, where the value of one (1) is added to the values of s_j except for the criterion that is ranked best; the value of one (1) is retained for it (Equation 1). The next step is to calculate the relative importance of the criteria, where the value q_j is divided by the value of k_j or that value. For the highest-ranked criterion, the values are retained, while, for example, for criterion C3, the value one is divided by the value k_j for that criterion (Equation 2). For example, for criterion C6, the calculation procedure is as follows:

$$q_{C6} = \left(\frac{1.06}{1.81} = 0.52, \frac{1.06}{1.81} = 0.52, \frac{1.06}{1.81} = 0.52\right) \tag{12}$$

After that, the aggregate value of the relative importance of the criteria is calculated and all q_j values are divided by that value, and the final weight is formed (Equation 3). Using the example of criterion C6, it is calculated as follows:

$$w_{C6} = \left(\frac{0.52}{5.26} = 0.10, \frac{0.52}{5.26} = 0.10, \frac{0.52}{5.26} = 0.10\right) \tag{13}$$

The results of the fuzzy SWARA steps showed that criterion C1 holds the greatest importance according to expert opinions, followed by criterion C3 (Table 7). Criterion C8 has the least importance.

Table 7
Results of the fuzzy SWARA method application

	s_j	k_j	q_j	w_j
C1	1.00, 1.00, 1.00	1.00, 1.00, 1.00	1.00, 1.00, 1.00	0.19, 0.19, 0.19
C3	0.06, 0.06, 0.06	1.06, 1.06, 1.06	0.94, 0.94, 0.94	0.18, 0.18, 0.18
C6	0.81, 0.81, 0.81	1.81, 1.81, 1.81	0.52, 0.52 ,0.52	0.10, 0.10, 0.10
C9	0.06, 0.06, 0.06	1.06, 1.06, 1.06	0.49, 0.49, 0.49	0.09, 0.09, 0.09
C10	0.00, 0.00, 0.00	1.00, 1.00, 1.00	0.49, 0.49, 0.49	0.09, 0.09, 0.09
C2	0.06, 0.06, 0.06	1.06, 1.06, 1.06	0.46, 0.46, 0.46	0.09, 0.09, 0.09
C4	0.00, 0.00, 0.00	1.00, 1.00, 1.00	0.46, 0.46, 0.46	0.09, 0.09, 0.09
C5	0.38, 0.38, 0.38	1.38, 1.38, 1.38	0.33, 0.33, 0.33	0.06, 0.06, 0.06
C7	0.06, 0.06, 0.06	1.06, 1.06, 1.06	0.31, 0.31, 0.31	0.06, 0.06, 0.06
C8	0.25, 0.25, 0.25	1.25, 1.25, 1.25	0.25, 0.25, 0.25	0.05, 0.05, 0.05
		sum	5.26, 5.26, 5.26	

Once the criterion weights have been determined, the extent to which individual alternatives satisfy the established criteria is assessed. To determine this, experts evaluate the alternatives using linguistic values (Table 8). The subsequent steps mirror those of the fuzzy SWARA method: transformation into fuzzy numbers and calculation of the average fuzzy value. This calculation yields an aggregated decision matrix, to which the steps of the fuzzy TOPSIS method are then applied.

Table 8
Expert evaluations of cloud services

Expert 1	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	BA	VG	VG	GO	GO	GO	ME	ME	VG	GO
A2	ME	GO	GO	GO	GO	GO	GO	GO	GO	GO
A3	GO	ME	ME	ME	ME	ME	GO	GO	ME	ME
A4	BA	GO	EG	VG	GO	VG	ME	ME	VG	EG
A5	VG	BA	BA	ME	GO	ME	ME	GO	BA	BA
A6	ME	GO	GO	GO	ME	GO	ME	ME	GO	GO
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Expert 16	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10
A1	BA	EG	EG	VG	VG	VG	GO	GO	EG	EG
A2	ME	VG	VG	VG	VG	VG	VG	VG	VG	EG
A3	VG	GO	GO	GO	GO	GO	EG	VG	GO	GO
A4	BA	GO	EG	VG	GO	VG	GO	GO	VG	EG
A5	EG	ME	ME	GO	VG	GO	GO	VG	ME	ME
A6	GO	VG	VG	VG	GO	VG	GO	GO	VG	EG

Given that fuzzy TOPSIS has been widely applied in previous research, the steps of this method will not be explained in detail. The first step involves normalizing the data in the aggregated decision matrix (Equation 4). Next, the normalized values are weighted using the corresponding criteria weights (Equation 5), followed by the determination of ideal and anti-ideal solutions (Equations 6 and 7). Finally, the deviations from these solutions are calculated (Equations 8 and 9), and the fuzzy TOPSIS values are determined (Equation 10). The results obtained through this method, based on expert evaluations, indicate that cloud service A6 achieved the best results, followed by cloud service A1 (Table 9). These two services stand out from the other cloud services. Cloud service A5 shows the poorest results in this analysis.

Table 9
Results of the fuzzy TOPSIS method

	S_i^+	S_i^-	C_i	Rank
A1	0.409	0.505	0.553	2
A2	0.385	0.463	0.546	3
A3	0.436	0.419	0.490	5
A4	0.427	0.478	0.528	4
A5	0.514	0.408	0.443	6
A6	0.370	0.481	0.565	1

To examine these results, a comparative analysis will first be conducted, as it utilizes the same decision matrix and criterion weights while employing the procedural steps of other fuzzy methods. The results of the comparative analysis reveal the greatest fluctuations regarding the top two ranked cloud services. The fuzzy TOPSIS and ARAS methods ranked cloud service A6 as the best, whereas the other methods ranked cloud service A1 as the best (Figure 1). This is because these two cloud services received nearly identical ratings; consequently, experts consider them the optimal choices for companies in Serbia. In addition to these ranking discrepancies, a difference was observed in the ranking produced by the MABAC method, where alternative A6 placed third while A2 placed second. The variations in the MABAC ranking stem from the normalization process it employs and the method used to weight the normalized values. Based on these results, experts recommend the use of cloud services A1 and A6.

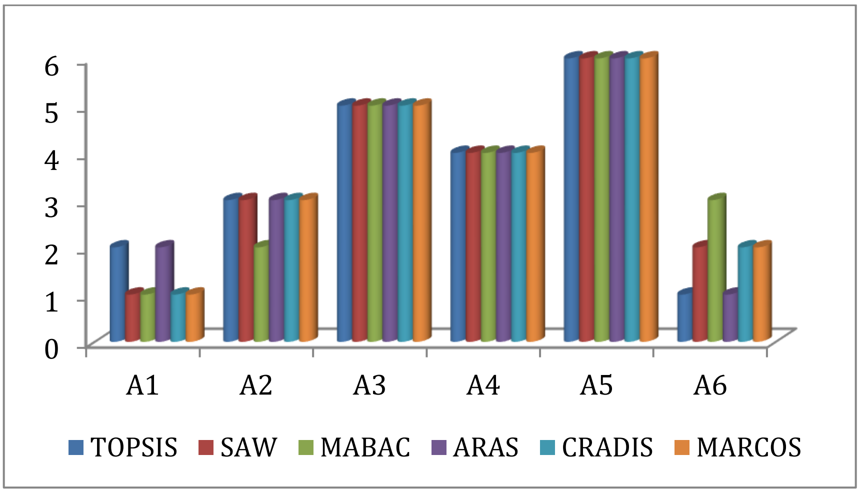

Fig. 1. Results of the comparative analysis

The sensitivity analysis employed 30 different scenarios, with rankings calculated using the fuzzy TOPSIS method. The results confirm that alternatives A1 and A6 are the best, as they were the only ones to secure the top rank across these scenarios (Figure 2). Beyond fluctuations in their rankings, the analysis revealed the strength of alternative A6 regarding criterion C1 (Cost); even when the importance of this criterion was reduced by 90%, alternative A6 still ranked fourth. Similarly, alternative A1 holds an advantage over alternative A2 regarding criterion C3 (security), as it ranked third even when the weight of this criterion was reduced. The sensitivity analysis showed no sensitivity for alternative A5, which was the lowest-ranked option in all scenarios. Alternative A3 ranked fourth in only one scenario and fifth in the others. Finally, the analysis confirmed that alternatives A6 and A1 yielded the best results, making them the superior choices among the cloud services examined.

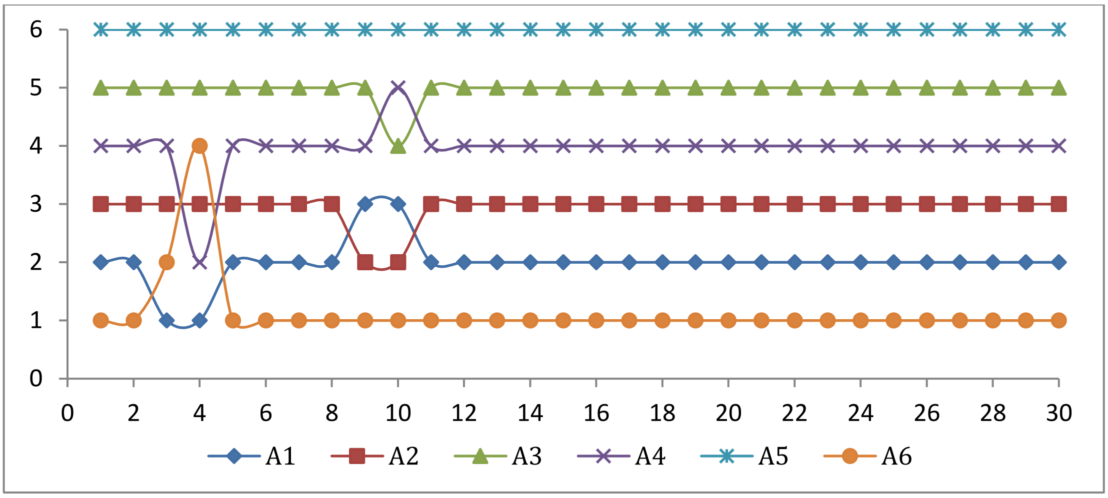

Fig. 2. Results of the sensitivity analysis

5. Discussion

This study utilized a developed hybrid MCDM framework, based on the integration of fuzzy SWARA and fuzzy TOPSIS methods, to select cloud services. The rationale for this decision-making approach stems from the inherent uncertainty associated with expert-based decision-making. A total of 16 experts from various sectors participated in the study, using linguistic ratings to determine criterion importance and rank the cloud services. Ten criteria and six cloud services were evaluated. The results were obtained through a hybrid fuzzy approach, employing SWARA to determine criterion weights and fuzzy TOPSIS to establish the ranking of the cloud services. This demonstrated that uncertainty in expert evaluations can be handled flexibly and efficiently, yielding stable and reliable results that serve as a basis for cloud service selection decisions.

The application of the fuzzy SWARA method, based on expert input, revealed that criterion C1 (cost) holds the highest importance, followed by criterion C3 (security). These two criteria stand out significantly compared to the others. These results reflect the specific characteristics of the cloud service market in Serbia, where cost and security are recognized as the most critical criteria for service selection. Similar findings were reported by Faiz and Daniel [9], who identified price and security as key factors in cloud service selection. These results were further corroborated by a study conducted by Kahraman *et al.,* [11], which also identified security and price as the most important criteria. In this study, criterion C8 - Flexibility, holds the least importance. This result can be explained by the fact that cloud services are inherently recognized as flexible; therefore, flexibility is not a decisive factor in their selection.

The results of the fuzzy TOPSIS method, based on expert evaluations, indicate that cloud service A6 performs best, followed by cloud service A1. These two services stand out from the rest. Experts identified them as services characterized by operational security and reliability, as well as strong standards compliance. They demonstrated the optimal balance between cost, security, and reliability. Although cloud service A5 offers the most favorable pricing, it ranked lowest due to inferior performance and security features. Similar results were obtained in studies conducted by Ghorui *et al.,* [8] and Jatoth *et al.,* [2], where security and reliability were the decisive criteria for ranking cloud services.

The comparative analysis revealed consistency across the various MCDM methods: fuzzy TOPSIS and ARAS ranked cloud service A6 as the best, whereas SAW, MABAC, CRADIS, and MARCOS ranked cloud service A1 as the best. Differences in rankings stem from variations in data normalization and aggregation procedures, as well as the specific steps involved in each method. However, given the experts' evaluations, the differences in final rankings were minimal, thereby validating the results obtained through the fuzzy TOPSIS method. A sensitivity analysis involving 30 scenarios confirmed that cloud services A6 and A1 hold an advantage over other services, as they were the top-ranked options across all scenarios. The analysis revealed that cloud service A6 is particularly sensitive to changes in the weight of criterion C1 (cost), whereas A1 is sensitive to changes in the weight of criterion C3 (security). Thus, it was demonstrated that these services offer the best balance between cost and data security, the most critical criteria in this study.

6. Conclusions

This study employed a hybrid MCDM framework based on the fuzzy SWARA and TOPSIS methods for cloud service selection. Results derived from expert evaluations indicated that cost (C1) and security (C3) are the most critical criteria in the selection process. Furthermore, the fuzzy TOPSIS method identified cloud services A6 and A1 as the top-ranked options; these services also demonstrated superior performance in supplementary analyses. This paper contributes to theoretical development by proposing a model for cloud service selection that enables a rapid and flexible decision-making process.

Additionally, it outlines the criteria applicable to this selection. In practical terms, the model is adaptable not only to cloud service selection but also to other decision-making scenarios, provided it is tailored to the specific process at hand. The findings offer guidance to decision-makers in organizations planning to utilize cloud services as part of their business digitalization efforts, highlighting the need to balance cost, security, and reliability.

Limitations of the study stem from the specific criteria, the number of experts involved, and the number of cloud services evaluated. Another limitation is the geographic focus on Serbia, which restricts the generalizability of the results. Consequently, future research should incorporate a broader range of criteria, including new ones that might better facilitate the decision-making process, and expand the scope to include additional cloud service providers and countries to enhance the generalizability of the findings.

Acknowledgement

This research was not funded by any grant

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] Araujo, J., Maciel, P., Andrade, E., Callou, G., Alves, V., & Cunha, P. (2018). Decision making in cloud environments: an approach based on multiple-criteria decision analysis and stochastic models. Journal of Cloud Computing Advances Systems and Applications, 7(1), 7. https://doi.org/10.1186/s13677-018-0106-7

[2] Jatoth, C., Gangadharan, G. R., Fiore, U., & Buyya, R. (2019). SELCLOUD: a hybrid multi-criteria decision-making model for selection of cloud services. Soft Computing, 23(13), 4701–4715. https://doi.org/10.1007/s00500-018-3120-2

[3] Abdel-Basset, M., Mohamed, M., & Chang, V. (2018). NMCDA: A framework for evaluating cloud computing services. Future Generations Computer Systems, 86, 12–29. https://doi.org/10.1016/j.future.2018.03.014

[4] Abdullah, S., Saifullah, & Almagrabi, A. O. (2023). An Integrated Group Decision-Making Framework for the Evaluation of Artificial Intelligence Cloud Platforms Based on Fractional Fuzzy Sets. Mathematics, 11(21), 4428. https://doi.org/10.3390/math11214428

[5] Gyani, J., Ahmed, A., & Haq, M. A. (2022). MCDM and various prioritization methods in AHP for CSS: A comprehensive review. IEEE Access: Practical Innovations, Open Solutions, 10, 33492–33511. https://doi.org/10.1109/access.2022.3161742

[6] Hosseinzadeh, M., Hama, H. K., Ghafour, M. Y., Masdari, M., Ahmed, O. H., & Khezri, H. (2020). Service selection using multi-criteria decision making: A comprehensive overview. Journal of Network and Systems Management, 28(4), 1639–1693. https://doi.org/10.1007/s10922-020-09553-w

[7] Rahimi, M., Jafari Navimipour, N., Hosseinzadeh, M., Moattar, M. H., & Darwesh, A. (2022). Toward the efficient service selection approaches in cloud computing. Kybernetes, 51(4), 1388–1412. https://doi.org/10.1108/k-02-2021-0129

[8] Ghorui, N., Mondal, S. P., Chatterjee, B., Ghosh, A., Pal, A., De, D., & Giri, B. C. (2023). Selection of cloud service providers using MCDM methodology under intuitionistic fuzzy uncertainty. Soft Computing. 27(5), 2403–2423 https://doi.org/10.1007/s00500-022-07772-8

[9] Faiz, M., & Daniel, A. K. (2024). A multi-criteria cloud selection model based on fuzzy logic technique for QoS. International Journal of System Assurance Engineering and Management, 15(2), 687–704. https://doi.org/10.1007/s13198-022-01723-0

[10] Monika, & Sangwan, O. P. (2022). A framework for evaluating cloud computing services using AHP and TOPSIS approaches with interval valued spherical fuzzy sets. Cluster Computing. 25, 4383–4396. https://doi.org/10.1007/s10586-022-03679-z

[11] Kahraman, C., Cevik Onar, S., & Oztaysi, B. (2022). Cloud service provider selection using interval-valued picture fuzzy TOPSIS. In INFUS 2022. Lecture Notes in Networks and Systems, 504, (pp. 498–507). Springer, Cham. https://doi.org/10.1007/978-3-031-09173-5_59

[12] Mostafa, A. M. (2024). A group multi-criteria decision-making approach based on the best-only method for cloud service selection. IEEE Access: Practical Innovations, Open Solutions, 12, 119946–119957. https://doi.org/10.1109/access.2024.3450280

[13] Tiwari, K., Sharma, A. K., & Tiwari, R. K. (2026). Integration of fuzzy BWM and G-TOPSIS for optimal cloud service provider selection under uncertainty. 2026 5th International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE), 1–8. https://doi.org/10.1109/ICDCECE68961.2026.11646063

[14] Liu, Z., Wang, D., Wang, W., & Liu, P. (2022). An integrated group decision-making framework for selecting cloud service providers based on regret theory and EVAMIX with hybrid information. International Journal of Intelligent Systems, 37(6), 3480–3513. https://doi.org/10.1002/int.22698

[15] Goyal, P., & Deora, S. S. (2025). Robust cloud service ranking with deep learning and multi-criteria analysis. Journal of Web Engineering, 24(5), 739-772 https://doi.org/10.13052/jwe1540-9589.2453

[16] Kumar, A., Singh, A. K., & Garg, A. (2023). Application of MCDM methods in cloud computing: A literature review. In Artificial Intelligence, Blockchain, Computing and Security Volume 1 (pp. 868–873). CRC Press. https://doi.org/10.1201/9781003393580-129

[17] Youssef, A. E. (2020). An integrated MCDM approach for cloud service selection based on TOPSIS and BWM. IEEE Access: Practical Innovations, Open Solutions, 8, 71851–71865. https://doi.org/10.1109/access.2020.2987111

[18] Tomar, A., Kumar, R. R., & Gupta, I. (2022). Decision making for cloud service selection: a novel and hybrid MCDM approach. Cluster Computing. 26(6), 3869–3887. https://doi.org/10.1007/s10586-022-03793-y

[19] T., T., Kalaiarasan, C., & Venkatesh, K. A. (2022). Cloud Provider Selection Based on Accountability and Security Using Interval-Valued Fuzzy TOPSIS. *International Journal of Decision Support System Technology (IJDSST), 14*(1), 1-15. https://doi.org/10.4018/IJDSST.286684

[20] Mandal, S., & Khan, D. A. (2022). Cloud-CoCoSo: Cloud model-based combined compromised solution model for trusted cloud service provider selection. Arabian Journal for Science and Engineering, 47(8), 10307–10332. https://doi.org/10.1007/s13369-021-06512-8

[21] Liu, M., Shao, Y., Yu, C., & Yu, J. (2020). A heterogeneous QoS-based cloud service selection approach using entropy weight and GRA-ELECTRE III. Mathematical Problems in Engineering, 2020, 1-17. https://doi.org/10.1155/2020/1536872

[22] Makwe, A., Kanungo, P., Kautish, S., Madhu, G., Almazyad, A. S., Xiong, G., & Mohamed, A. W. (2024). Cloud service prioritization using a Multi-Criteria Decision-Making technique in a cloud computing environment. Ain Shams Engineering Journal, 15(7), 102785. https://doi.org/10.1016/j.asej.2024.102785

[23] Zhang, S., Tang, J., Meng, F., & Yuan, R. (2021). A group decision making method with interval-valued intuitionistic fuzzy preference relations and its application in the selection of cloud computing vendors for SMEs. Informatica, 32(1), 163-193. https://doi.org/10.15388/20-infor416

[24] Keršulienė, V., Zavadskas, E. K., & Turskis, Z. (2010). Selection of rational dispute resolution method by applying new step-Wise Weight Assessment Ratio Analysis (Swara). Journal of Business Economics and Management, 11(2), 243–258. https://doi.org/10.3846/jbem.2010.12

[25] Hwang, C. L., Yoon, K. (1981). Multiple Attribute Decision Making: Methods and Applications. Springer-Verlag, New York. https://doi.org/10.1007/978-3-642-48318-9