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An Integrated MCDM Approach for Cloud Service Selection Based On TOPSIS and BWM

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Abstract: Because of the rapid advancement of cloud computing services and the proliferation of CSPs, many businesses have required assistance in selecting a cloud service provider. When comparing the services provided by different CSPs, many independent criteria should be considered. It represents multi-criteria decision-making (MCDM). Given the vast diversity of these services, choosing the best cloud service provider (CSP) becomes a major challenge. Due to this, we have to precisely evaluate the services of several CSPs. The selection of the best CSP is thus a complex multi-criteria decision (MCDM) that needs to be adjusted efficiently. In this paper, we propose a feasible, efficient, and consistent MCDM approach based on relative preferences for criteria and alternatives. The proposed method includes Techniques for Order of Preference by Similarity to the Ideal Solution (TOPSIS) and the Best or Worst Method (BWM).

Keywords: Cloud Computing, cloud service provider, Techniques for Order of Preference by Similarity to the Ideal Solution, Best or Worst Method.

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1. Introduction

Cloud computing is a relatively new concept in the field of computer science that aims to make the benefits of computers more accessible to a wider audience through the provision of various computer-related services. Utilization-based pricing for data storage, deployment models, infrastructure, platforms, and resources its main goal is to make it easier to store and share data over the internet in a safe and trustworthy manner. This programmed known as an agent, serves the interests of its users. Intelligent agents are capable of doing a wide range of tasks, including those that are routine, repetitive, time-consuming, or simply too much for a human to handle on their own, such as learning, computing, or making judgments.

A growing number of companies are looking to cloud computing (CC) as a viable alternative to maintaining their own in-house data centres. Our concept of how to acquire flexible, readily available computing resources with low administration overhead has been radically altered as a result. As a result, businesses are liberated to concentrate on what they do best while outsourcing IT infrastructure management to CSPs. Companies providing leasing services are known as CSPs. Infrastructure as a service, platform as a service, and software as a service are all examples of cloud computing services that can be provided on a pay-as-you-go basis and in response to fluctuating consumer demand. There is a contract in place called a Service Level Agreement (SLA) that governs the relationship between customers and CSPs. In response to the rising demand for cloud services, a growing number of IT service providers are vying for consumers' business by providing increasingly sophisticated cloud solutions at competitive prices.

As a result of the abundance of options, most cloud clients are at a loss when it comes to selecting the best cloud service provider (CSP). When comparing the services of different CSPs, it is important to take into account a wide range of characteristics, not all of which are clearly quantifiable. Thus, picking the appropriate CSP is an intricate MCDM problem that must be solved effectively.

Prior research on this topic has found that MCDM approaches are impractical when it is difficult or nonsensical to quantify alternatives over criteria, or they are computationally expensive and inconsistent when

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comparing alternate preferences and criteria. In this study, we offer a unique MCDM method that can be applied in practice, is time-efficient, and yields consistent results when weighing relative preferences across criteria and options. As part of the suggested method, a method is included for ranking preferences in terms of how closely they match the optimal answer. (TOPSIS) and the "Best Worst Method" (BWM) to rate CSPs according to service-defining evaluation criteria. An application scenario was used to test and validate the integrated strategy, proving its efficacy and correctness. In addition, we compared our method with the standard method for MCDM.

Main Contribution of the paper is:

- To develop an integrated MCDM approach for service selection based on TOPSIS and BWM.
- This paper considers QoS factors of the criteria of different alternatives as the input for which we have to make a decision.
- Evaluation of alternatives with TOPSIS and determination of the final rank.

The remaining paper is organized as follows: Section 2 represents a literature review; Section 3 presents a proposed model; Section 4 presents a result analysis; and Section 5 presents concussion.

2. Literature Review

Research into the cloud service selection problem has increased in recent years, with some studies using MAUT approaches and others employing pair wise comparison strategies. However, many straightforward MCDM methods are being incorporated into new hybrid systems. When hybrid methods are used, consumer confidence is boosted, and final decisions are more precise.

The multi-criteria decision-making (MCDM) cloud service selection framework (TOPSIS)[ ] in this study is based on the best-only method (BOM) and a method for ranking preferences by how close they are to the best answer. The BOM compares each cloud service provider (CSP) to itself and to other CSPs on each criterion to determine a weight for each criterion; TOPSIS then uses these weights to rank the CSPs. In order to demonstrate the effectiveness and precision of the proposed framework, an evaluation and validation have been conducted through a use-case model. In addition, the effectiveness and consistency of the created framework were compared to those of the analytical hierarchical process (AHP), a well-known MCDM method. The findings suggest that only a quarter as many comparisons are needed as with the AHP method when using the proposed framework. Meanwhile, the CR for the proposed framework is a meagre 0%, whereas it is 38% for AHP. To sum up, the suggested approach outperforms AHP in terms of both computational complexity and consistency, suggesting it is more effective and reliable.

A unique MCDM strategy based on relative preferences for criteria and options is proposed in this study [2]. A combination of the Best Worst Method (BWM) and the Technique for Order of Preference by Similarity to an Ideal Solution (TOPSIS) is used in the suggested method to rank CSPs according to evaluation criteria that are indicative of the quality of their services. The efficiency and accuracy of the integrated strategy have been proven through testing and validation using a use-case scenario. To further demonstrate the merits of our proposal, we have contrasted it with the current gold standard in MCDM methodology, Analytical Hierarchical Process (AHP). Based on the results, it's clear that the proposed method is both faster and more reliable than AHP. It requires less computing time and gives more consistent results.

To support the decision-maker in comparing and contrasting available cloud services, the authors of this research [3] suggest a hybrid multi-criteria decision-making technique. We offer a new method that integrates subjective and objective criteria into a single evaluation. Eligible CSPs are then ranked in accordance with their prioritized list, which is derived from the findings of the comprehensive assessment. A real-world case study verifies the simulation results, adding more weight to the claims that the suggested method improves user happiness and works well in terms of precision and dependability. In order to demonstrate the reliability and consistency of our method, we conclude with a sensitivity analysis.

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, AHP, ANP, MAUT, ELECTRE, SAW, and rank voting method are the most common MCDM approaches for cloud service selection in the literature. Kumar et al. [4] developed a cloud service selection framework based on AHP and TOPSIS. They adopted a real-time dataset from Cloud Harmony 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. [5] 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. [6] 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 [7] 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

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between these various types of multi-attribute preference functions are investigated.

Govindan et al. [8] 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. [9] 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. [10] 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 , IaaS services, and general cloud services. 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. [11] to compare and rank three IaaS cloud services using the SMI criteria. 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. [12] 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 [13]. 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.

3. Proposed Method

In this paper, we provide a comprehensive MCDM methodology for choosing cloud service providers. The proposed framework utilizes the BOM approach to determine criteria weights and the weights of alternatives in relation to each criterion, and then TOPSIS ranks the candidates for cloud storage based on these weights (CSPs). The BOM method relies on a single criterion determination before subjecting it to several pair wise comparisons. In this way, the matrix's judgments are entirely consistent, and all of its members satisfy the property in (9). There is a flowchart depiction of the integrated framework's procedures in Fig. 1.

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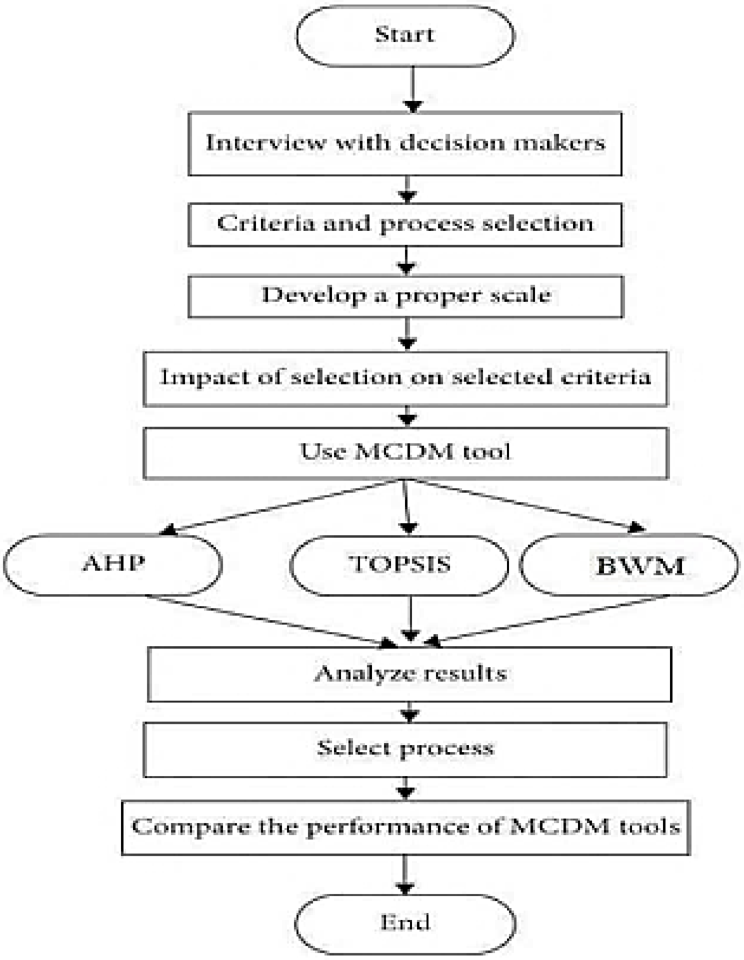

Figure 1: Flow model of proposed work

Step 1: Create an evaluation matrix consisting of m alternatives and n criteria with the intersection of each alternative and criteria.

Step 2: Calculating Normalized Matrix: We normalize each value by making it: where m is the number of rows in the dataset and n is the number of columns. I vary along rows and j varies along the column.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{k=1}^{m} x_{kj}^2}},$$
$$i = 1, 2, \ldots, m,$$
$$j = 1, 2, \ldots, n$$

Step 3: Calculate the weighted normalized decision matrix

Step 4: Calculating Ideal Best and Ideal worst and Euclidean distance for each row from ideal worst and ideal best value. First, we will find out the ideal best and ideal worst value: Now here we need to see the impact, i.e. is it '+' or '-' impact. If '+' impact Ideal best for a column is the maximum value in that column and the ideal worst is the minimum value in
that column, and vice versa for the '-' impact

Step 5: Now we need to calculate Euclidean distance for elements in all rows from the ideal best and ideal worst, Here d_{iw} is the worst distance calculated of an i^{th} row, where $t_{i,j}$ is element value and $t_{w,j}$ is the ideal worst for that column. Similarly, we can find dib, i.e. best distance calculated on an i^{th} row

$$d_{iw} = \sqrt{\sum_{j=1}^{n} (t_{ij} - t_{wj})^2},$$
$$i = 1, 2, \ldots, m.$$

Step 6: Calculating Topsis Score and Ranking. Now we have Distance positive and distance negative with us, let's calculate the Topsis score for each row on basis of them. TOPSIS Score = diw / (dib + diw) for each row. Now rank according to the TOPSIS score, i.e. higher the score, better the rank.

BWM:

In pair wise comparison-based methods we either have methods for which we use a single vector or a full matrix. Although using one vector for the input data makes the method very data-efficient, the main weakness of methods based on only one vector is that the consistency of the provided pairwise comparisons cannot be checked. On the other hand, although using a full matrix provides the possibility of checking the consistency of the provided

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pairwise comparisons, methods which are based on full pairwise comparison matrix are not data efficient. Asking too many questions from the DM, which occurs in the case of full matrix, might even contribute to the confusion and inconsistency of the DM. BWM stands in the middle. That is to say, it is the most data-efficient method which could, at the same time, provide the possibility of checking the consistency of the provided pairwise comparisons. As the two vectors are formed with considering two specific reference criteria, BWM should not be seen as a case of incomplete pairwise comparison matrix.

4. Result analysis

For this paper implementation we have been deployed this project in following system specification i.e the following few tools have been used to perform this analysis 1. Python IDE. 2. AWS 3. Jupyter 4. Python Libraries: i. Numpy ii. Pandas iii. Matplotlib iv. Sklearn

These weights are calculated using the BW (best worst) method.

```
Weights : [0.58938514 0.17115996 0.14443888 0.09501602]

Step 1
[[250.  16.  12.   5.]
 [200.  16.   8.   3.]
 [300.  32.  16.   4.]
 [275.  32.   8.   4.]
 [225.  16.  16.   2.]]
```

This is the evaluation matrix where columns are criteria and rows are alternatives.

```
Step 2
[[0.44280744 0.30151134 0.42857143 0.5976143 ]
 [0.35424595 0.30151134 0.28571429 0.35856858]
 [0.53136893 0.60302269 0.57142857 0.47809144]
 [0.48708819 0.60302269 0.28571429 0.47809144]
 [0.3985267  0.30151134 0.57142857 0.23904572]]
```

This is the normalized matrix.

```
Step 3
[[0.26098413 0.05160667 0.06190238 0.05678293]
 [0.2087873  0.05160667 0.04126825 0.03406976]
 [0.31318095 0.10321334 0.0825365  0.04542635]
 [0.28708254 0.10321334 0.04126825 0.04542635]
 [0.23488571 0.05160667 0.0825365  0.02271317]]
```

This is the weighted normalized matrix.

```
Step 4
[0.2087873  0.05160667 0.04126825 0.02271317] [0.31318095 0.10321334 0.0825365  0.05678293]
```

This is best and worst alternative

```
Step 5
[0.06565839 0.01135659 0.12561942 0.09648461 0.04882823] [0.07624647 0.12561942 0.01135659 0.05013151 0.09977044]
```

This is the Euclidean distance

```
Step 6
[0.46269304 0.08290931 0.91709069 0.65807644 0.32859128] [0.53730696 0.91709069 0.08290931 0.34192356 0.67140872]
```

This is the TOPSIS similarity vector.

```
worst_similarity        [0.46269304 0.08290931 0.91709069 0.65807644 0.32859128]
rank_to_worst_similarity        [2, 5, 1, 4, 3]
best_similarity  [0.53730696 0.91709069 0.08290931 0.34192356 0.67140872]
rank_to_best_similarity  [3, 4, 1, 5, 2]
```

This is the rankings of best and worst similarities.

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5. Conclusion

This paper describes a novel MCDM approach that is feasible, efficient, and consistent using relative preferences for criteria and alternatives. The proposed approach integrates the Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) and the Best Worst Method (BWM) to rank CSPs using evaluation criteria characterizing their services. BWM calculates the criteria weights and the relative scores of alternatives concerning those criteria. TOPSIS uses these acquired values to rank the cloud services. The proposed approach has been tested and validated through a use-case scenario, demonstrating its effectiveness and correctness. We have compared the proposed method to the most commonly used MCDM (i.e., AHP). The results showed that our proposed approach outperformed AHP in terms of computational complexity and consistency; therefore, it is more efficient and reliable. The future work may be expanded to include the integration of BWM with different MCDM methods like AHP, ELECTRE, PROMETHEE, and Gray Theory in the cloud service selection problem and other applications.

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