International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. 12, No.1 (Aug-2022)

https://dx.doi.org/10.12785/ijcds/120136

A Multi-Criteria Dual Membership Cloud Selection Model based on Fuzzy Logic for QoS

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Received 21 Sep.2021, Revised 5 Jul. 2022, Accepted 15 Jul. 2022, Published 6 Aug. 2022

Abstract: The use of cloud computing in various data-centric applications such as wireless sensor networks (WSN) has attracted a large number of users because the cloud integrates various features in the applications such as scalability, availability, security, etc. The adoption of on-demand services of the cloud has raised competition among various cloud service providers (CSPs).The various CSPs charge different subscription charges for their services, such as storage space and virtual processors. Hence, the selection of the most suitable cloud is a must. In this paper, a multi-criteria dual-membership-based fuzzy technique (MC-DMFT) is proposed to improve cloud users' QoS experience and address the hurdle of choosing an appropriate cloud service. We have used the MC-DMFT method to define the phases of the overall process involved in the cloud service selection and calculated the rank values for different users for QoS. Existing approaches are not proficient enough, and they require a very complex computation process. The proposed approach uses the concept of fuzzy technique to rank various cloud service providers based on capacity, pricing, security, performance, and maintenance as key parameters. The comparative analysis shows the effectiveness and potential of the proposed method.

Keywords: Fuzzy, QoS, Rank, Membership function,SaaS

1. INTRODUCTION

In the past few years, due to the technological enhancement in cloud computing has increased its popularity worldwide. The traditional computing systems require in-house system infrastructure that requires lots of capital investments and computational expertise. Cloud computing, on the other hand, offers undeniable benefits-oriented services in terms of availability, reliability, scalability and cost [1]. The concept of cloud computing comes from various technologies, which makes people confused with other similar types of computing systems. In comparison to various existing technologies, the cloud offers more benefits in terms of ease of usage and cost of service subscriptions. It has significantly enhanced the computing power of various application domains such as Wireless Sensor Network (WSN) and the Internet of Things (IoT) [2]. Cloud computing enables businesses to concentrate on their core activities rather than worrying about the technology and upkeep of their computing infrastructure. It helps organizations to more effectively enhance the functionality of their software, such as the required amount of storage, low maintenance cost, and the capability to meet changeable and unforeseen demands. In cloud computing, consumers are required to make payments based on the amount of time they spend using the service. Due to the prompt increase of online users, an increasing number of CSPs are accessible in the market, resulting in intense rivalry among CSPs [3]. It is a very tough task for a single CSP to deliver quality-driven cloud services in the current dynamic environment, and it is much more difficult for users to choose the most suitable cloud that meets their needs for cloud usage [4], [5]. In addition, cloud users are also not aware of how their requirements can be better optimized. In this context, the different criteria of QoS play an important role to be enabled in identifying and evaluating various CSPs. The QoS-based criteria explain the functional and non-functional features of a cloud service offered by a CSP, such as reliability, response time, performance, and security [6]. In order to explain the service selection problem, we can take the example of cloud service providers and cloud customers. A cloud user or a customer compares the offered services of various CSPs using the QoS criteria. Hence, this problem situation comes under the multi-criteria decision-making (MCDM) category [7]. Fig. 1 shows Cloud-based service models, each with its worldwide popular services

A significant study has been conducted in recent years on the selection and acceptance of cloud computing in a variety of applications, including sensor based cloud computing [8]. Various researchers have proposed numerous approaches for the measurement of qualitative behaviors, and a different set of rules and protocols have been proposed to get the quantifiable representation of different QoS attributes. Their proposed approaches are not proficient

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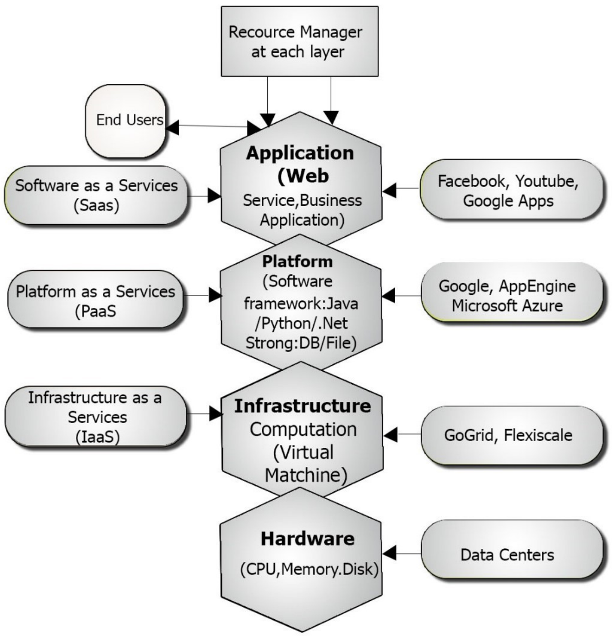

Figure 1. Cloud Computing Services

enough to capture a variety of ambiguity in the perspective of requirements to users, such as AHP, which suffers from rank reversal problems when more parameters are included as input criteria. On the other hand, this size is incapable of capturing a variety of ambiguous perspectives on cloud client requirements [9]. At the present time, there is no simple and effective technique available that enables users to filter out different cloud services based on their imprecise preferences for satisfying their quality-oriented service needs.

To address and overcome this multi-criteria-based cloud service selection problem, we developed a fuzzy logic-based cloud service ranking technique that is capable of evaluating and ranking various cloud-oriented services provided by different CSPs.

The contribution of the paper is described as follows:

(1) Assessment of criteria through a number of functional and non-functional characteristics that play a key role in the assessment of the services offered by a CSP

(2) A novel Multi-Criteria Dual Membership Function-based Fuzzy Technique (MC-DMFT) to calculate the priority likelihood of the QoS criterion and rank different CSPs.

(3) The performance of the proposed approach is tested using real-world cloud datasets with similar existing techniques.

The paper is divided into the following sections: section 2: contains related work, section 3: role of parameters in cloud service ranking, section 4: proposed methodology, section: 5 validation, section: 6 simulation, section: 7 conclusion and future work.

2. RELATED WORK

Numerous researchers have tried to find solutions to QoS-based cloud service selection issues as the quantity of CSPs has increased in a few years[10]. The SMI-CLOUD framework was proposed [11] to gather and estimate three IaaS-based cloud computing services. To calculate the significance of the criterion and assess the three IaaS services, the authors employed the AHP approach. This approach was primarily focused on three fundamental stages: issue decomposition, priority assessment, and rating of IaaS service suppliers. A framework linking the selection objective, the QoS criteria, and the service providers is built in the first step. The second step employed a pairwise matrix comparison to determine the weights of the criterion. The ranking of IaaS cloud service suppliers is determined in the final stage using the weight of the criterion. Several empirical key performance-based indicators for QoS are presented by CSMIC in this research, and various CSPs utilize these KPIs to analyze them. The use of AHP also makes it possible to estimate interconnections across metrics and measure criteria weights on the basis of the user's desire.

The optimal database server provider was evaluated using the AHP technique based on the needs and inclinations of cloud customers. A system with three critical criteria along with seven sub-criteria is employed in their work. In[12], authors conducted an IaaS-based cloud evaluation using the evolutionary algorithm in conjunction with the AHP technique. In this article, a Cloud-Genius paradigm with 15 QoS criteria was proposed for evaluating the top IaaS service providers. AHP and fuzzy logic have been used in various works of literature to address ambiguities in the choosing of cloud services[13].In order to tackle ambiguity and partiality during quality evaluation, a user functionality reliability measuring technique was proposed[14], [15]. This approach used the fuzzy-AHP technique. In this effort, the user's characteristic model was used to comprehensively evaluate the QoE (Quality of Experience) influencing variables. A fuzzy-AHP approach was developed in the study [16] to evaluate various cloud services on the basis of various QoS criteria. In this scenario, it was modified to develop a foundation for a hierarchy model to comprise repute as a new standard for excellent quality. A fuzzy-AHP technique incorporating a Balanced Scorecard (BSC) was presented for cloud service selection challenges[17]. Evaluation of the IaaS cloud platform and the selection of the top cloud services on the basis of 18 financial and non-financial criteria were the goals of the suggested technique. Few studies have evaluated the quality of cloud services using the "5-point Likert" scale [cite] and Saaty's fundamental scale[18].

An enhanced DEA and SDEA technique has been used in [19], to choose the suitable cloud services among a variety of cloud services depending on client specifications.

In [20], the author built a SELCLOUD model to assess and rate various cloud services by using a modified version of TOPSIS named M-TOPSIS and AHP approach. Furthermore, the authors used the M-TOPSIS approach to rank several cloud alternatives while evaluating the significance of the QoS characteristic using the AHP methodology. However, the majority of research makes the assumption that QoS characteristics are maverick. The numerous MCDM approaches AHP, ANP, and TOPSIS have been used by the authors to build their time-conscious discretion technology.

This section also includes a short summary in tabular format to represent various techniques, algorithms, QoS parameters used, the addressed service models (SaaS, PaaS, IaaS), and the approach proposed by various authors. Table 1 shows the existing models proposed by various authors.

3. ROLE OF PARAMETERS IN CLOUD SERVICE RANKING

Going through the literature review in section-2, there are a number of parameters that are used to rank cloud resources, the most important of which are as follows:

A. Availability

It is the period during which the service is active. It is also reflected by the functional and committable state of the cloud service. The availability can be computed using Eq. 1 as:

$$CloudServiceAvailability(CSA) = \frac{C_{Sot}}{C_{Sot} + C_{Srt}} \quad (1)$$

C_{Sot}: cloud service operational time, C_{Srt}: cloud service restoring time.

B. Reliability

The statistic is used to assess a cloud service ability to meet its SLA(Service Level Agreement) criteria. It reflects a service's uninterrupted operation at a given time and condition. The reliability and mean time of failure(MoF) of Cloud service is computed using Eq. 2 and Eq. 3 as:

$$Reliability(RT) = P_V \times A_{MOF} \quad (2)$$

$$MoF = \frac{Total\ sum\ of\ time\ between\ Failures}{Total\ Failures\ count} \quad (3)$$

P_V: Probability of violation, A_{MoF}: Assured mean time of failure, MoF: Average time spent between successive flaws in cloud service.

C. Stability

Stability is characterized by fluctuations in software instance efficiency or platform performance. Variation to

TABLE I. Various cloud service selection models

Reference and Year	Model	Technique/ Algorithm	QoS Parameters	Cloud	Approach
[21] (2014)	Risk mangement between CSP and cloud server	SELCSP Framework	Risk, Trust	SaaS	Trust
[22] (2015)	Sugeno Fuzzy inference system (FIS)	Fuzzy-AHP	Cost, Agility and Performance	SaaS PaaS IaaS	Multi-Criteria
[23] (2015)	Hierarchical based Decision making	ANP	Sub-criteria such as cloud provider name	SaaS PaaS IaaS	Multi-Criteria
[24] (2016)	Trust Modelling	Trust Approach	Capacity, Cloud Security	SaaS PaaS IaaS	Trust
[25] (2020)	Trust Estimation	Genetic Algorithm	Availability, Security, Dependability	IaaS	Multi-criteria
[26] (2020)	Qos aware selection	Hybrid Approach	Security, Usability, Performance	SaaS PaaS IaaS	Multi-criteria
[27] (2020)	Trust based Model	Fuzzy Technique	Capacity, Cost, Performance	SaaS PaaS IaaS	Multi-criteria
[28] (2021)	Modified-TOPSIS	RE-TOPSIS	Cost, Performance, Scalability	SaaS	Multi-criteria

achieve performance stability of specified resource instances is calculated using Eq. 4.

$$Variability(VR) = \sum \frac{\frac{\alpha_{avg\ ,i-\alpha_{SLA,i}}}{T}}{n} \quad (4)$$

α: computational storage network element of the cloud resource, $\alpha_{avg,i}$: avg. performance of user 'i' who opted for the cloud service, $\alpha_{SLA,i}$: promised service values, T: total service time, n: number of cloud users.

D. Response time

This is the time it takes for a cloud service request to be processed. This is the time to construct a virtual machine (V_m) instance + Virtual machine initialization time (t) + response time. The response time of Cloud service is computed using Eq. 5 as:

The service response time is:

$$(CSRT) = (T_{CCR} - T_{SR}) \quad (5)$$

T_{CCR}: Time of CC request received by CSP, T_{SR}: Time of start of response by CSP, The metric range of CSRT is CSRT > 0, here lesser the value represents the quicker response time.

E. Flexibility

The process of implementing a design when a variation arises either within or externally. Determining the usefulness and correctness of cloud services during runtime is known as dynamic discovery (D_D), and it can be computed using Eq. 6. Dynamic adoption (D_A) refers to a CSP's capacity to modify services based on user demands, and it can be computed using Eq. 7. Variant Coverage (V_C) measures the number of DPs that may be purchased by the user. The rate for mismatch resolution (M_{RR}) measures how many inconsistencies can be resolved.

$$DynamicDiscoverability(D_D) = \frac{S_I}{T_I} \quad (6)$$

$$DynamicAdaptability(D_A) = (W_{MR} * M_{RR}) + (W_{VC} * V_C) \quad (7)$$

S_I : No. of Suitable Interfaces, T_I : Total no. of Interfaces to Determine, W_{MR} and W_{VC}: weights of M_R and V_C, The total sum of the weights W_{MR} and W_{VC} is 1, The range of weight is computed within the range of 0 to 1.

F. Scalability

In the cloud, scalability (S_c) is defined as the capacity of the cloud infrastructure to accommodate huge number of concurrent user requests. It can also be define as a cloud-based service capacity to expand in response to a high volume of requests. Eq. 8 is used to compute the scalability of a Cloud service.

$$S_c = \sum_{i}^{m} \sum_{j}^{n_i} (proportion\ of\ increase\ in\ R_{ij}) \quad (8)$$

R_{ij}: resource j which needs to be improved on cloud service i, m: the number of cloud services opted by the user, n: the number of cloud resources allocated to an individual cloud service.

G. Transparency

It's defined by the extent to which the cloud's functionality is exaggerated in response to service changes. Additionally, the degree to which these impacts occur may be assessed. Requests for cloud services are defined by the transparency (T_P) of the information provided. Eq. 9 can be used to calculate the scalability of a Cloud service.

$$T_P = \sum \frac{1}{n} + \sum \frac{Time\ for\ service\ affect\ i}{such\ occurrences\ count} \quad (9)$$

n: number of cloud services, i: represents cloud customer.

H. The novelty of the work

The literature review shows various authors have utiized MCDMs to describe various approaches to evaluating cloud computing services. There are various methods available, each claiming to address the dilemma of the service selection of a CSP. The extensive scope and subjectivity of these approaches also raise questions about their effectiveness and practical use. Several recent studies are insufficient or unsatisfactory. The literature research (Table 1) revealed that AHP or ANP is used to compute the criterion weight in most current studies. They interrupt the decision-making process and raise concerns about their legitimacy and trustworthiness. As an example: (1) Increasing the number of decision-making conditions complicates their application and computing, lowering total performance of the system. (2) It is very tuff to create appropriate comparisons between circumstances. (3) Rank reversal is a significant shortcoming in both systems. (4) Unable to cope effectively with the subjective information and ambiguity of cloud service choosing. We have proposed a fuzzy-based approach for the CSP selection problem that solves some of the issues that are left open for research.

4. Proposed Methodology

In this section, we have elaborated on the Multi-criteria selection technique and working of the proposed model for handling cloud customers' ambiguous preferences when it comes to QoS requirements. The main key methodology of the proposed model is the use of using of Multi-criteria Dual Membership based fuzzy technique (MC-DMFT).

A. Fuzzy Definition:

Given that a point ”p” exists in the Region ”U” that lies in a fuzzy set ”F”, the degree of membership (DoM) of the fuzzy set ”F” is expressed by the Eq. 10.

$$0 \leq \mu_F(k) \leq 1 \tag{10}$$

The fuzzy technique is a multi-valued logic (logic with several values) technique that is based on the principle of fuzzy set theory. In the proposed work, it is used to choose the appropriate cloud for the customers depending on their requirements and other selected characteristics.

B. Schematic Diagram

We have elaborated on the proposed method that handles the vagueness of the user preferences based on different QoS criteria. The subsection describes the cloud service selection process as follows:

The proposed approach is shown using the schematic diagram using Fig. 2. The whole methodology of cloud selection and recommendation includes three major phases:

(1) Selection and establishment of the input parameters.

(2) Construct a Fuzzy rule base and define the fuzzy rules.

(3) Apply the DMFT technique to compute the rank.

C. Methodology

Phase 1: Selection and establishment of the input parameters

In this phase, different parameters and their values are collected in a meaningful order. Going through the literature survey through Table 1, the proposed model for Cloud ranking involved the use of five Quality of Service (QoS) parameters: capacity of primary memory offered by a CSP, cost of subscription plan offered by a CSP for various cloud-based services (SaaS, PaaS, IaaS), the performance of database and processor available in the cloud subscription, security service offered by the cloud in terms of different levels (very low to very high), and maintenance time of cloud in fixed intervals is selected as input criteria to evaluate as CSP for the cloud allocation process. The proposed model used the ’Mamdani’ FIS for flow control, which has been incorporated in the proposed model. The dataset (Sidhu and Singh 2017) used for the model is shown in Table 2 as a reference where C_1, C_2,......, and C_5 are different Clouds. Taking into consideration the attributes, our model used the data listed in Table 2 of different CSPs

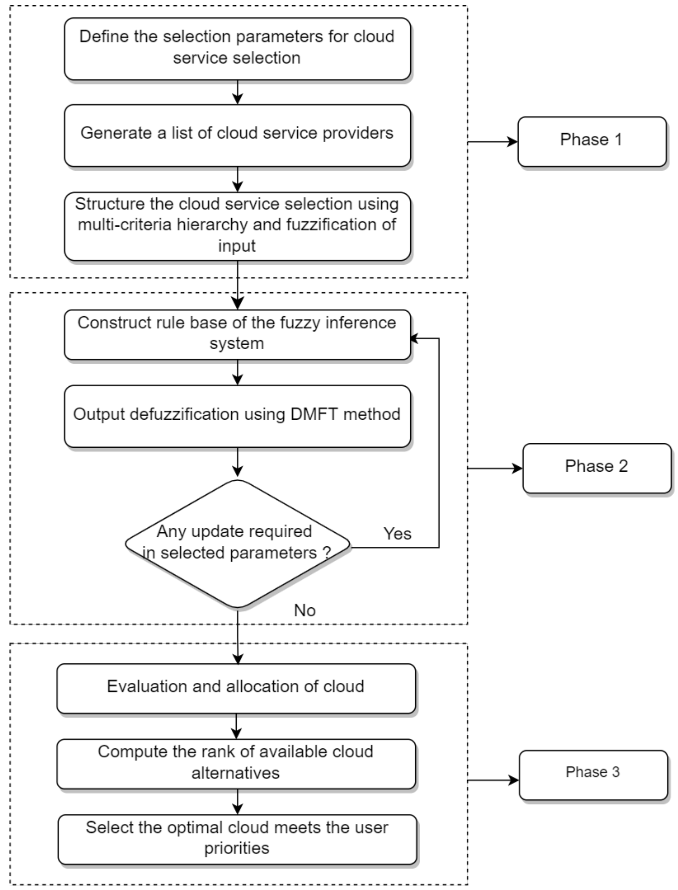

Figure 2. Schematic block diagram of the proposed methodology

TABLE II. Cloud subscription plans of different CSPs

Parameter	Sub-parameter	C1	C2	C3	C4	C5
Capacity	RAM (GB)	15	14	15	13	14
	C.P.U (GHz)	9.6	12.8	8.8	9.3	10.2
Cost	Vm Cost ($/month)	162.7	97.1	141	110.2	117.1
	Storage (TB/month $/GB)	0.02	0.03	0.03	0.04	0.03
Performance	Database performance (%)	55.0	68.0	65.0	75.0	72.0
	Max. C.P.U performance Score	2500	3100	3600	3800	4000
	Max. Network performance (Mbps)	1000	2100	2200	2700	3000
Security	Avg. Strength	0.6	0.5	0.8	0.7	0.8
Maintenance	Up-time (%)	99.90	99.59	99.92	99.45	99.97
	Free Support (Boolean)	Y	Y	N	N	Y

as a reference to construct the proposed models.

Moreover, crisp values are simply converted into corresponding fuzzy values. The MC-DMFT continues with the fuzzification method in this phase by applying a combination of triangular and trapezoidal membership function concepts (due to simplicity and precisely capturing of input values). The range values of each crisp value is denoted by initializing the range values of the corresponding fuzzy input variables. The following are the crisp input values for various parameters, as well as their fuzzy values.

1) Capacity

The capacity is determined by the user's RAM needs. Table 3 shows the input linguistics and their precise input range values using trapezoidal MF. The range value is calculated using the Table 2 dataset. Capacity is denoted by three linguistic terms: reasonable (low), good (Medium), and extensive (high). Eq. 11 represents the selection of capacity using the Fuzzy system.

$$\mu_{\text{capacity}} = \max\left(\left(\min \frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \tag{11}$$

TABLE III. Membership of Capacity

No.	Linguistic Term	Values(Gigabyte)
1	Extensive	[24,28,36,40]
2	Good	[7,15,20,25]
3	Reasonable	[0,0,6,8]

Fig. 3 depicts a fuzzy graph expressing the membership input range 'capacity' using trapezoidal MF to represent the membership input range 'capacity.'

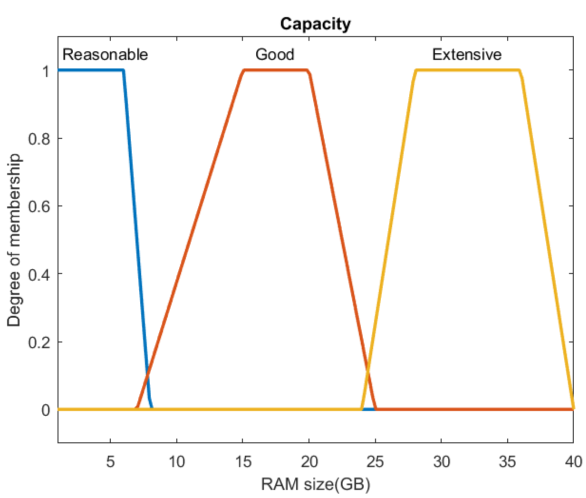

Figure 3. The capacity of RAM memory

2) Cost

According to our findings, one of the most crucial considerations when selecting cloud service providers is pricing. Users want to be able to obtain appropriate cloud services for the least amount of subscription charges possible. Table 4 shows the corresponding fuzzy values of each crisp input range value obtained by employing the trapezoidal membership function (MF).

TABLE IV. Membership of Cost

No.	Linguistic Term	Values ($/month)
1	Low	[0,0,90,100]
2	Reasonable	[90, 100, 110, 120]
3	High	[110, 120, 140, 150]
4	Very High	[150, 170, 180, 200]

Fig. 4 shows a fuzzy graph of the membership function 'cost'.

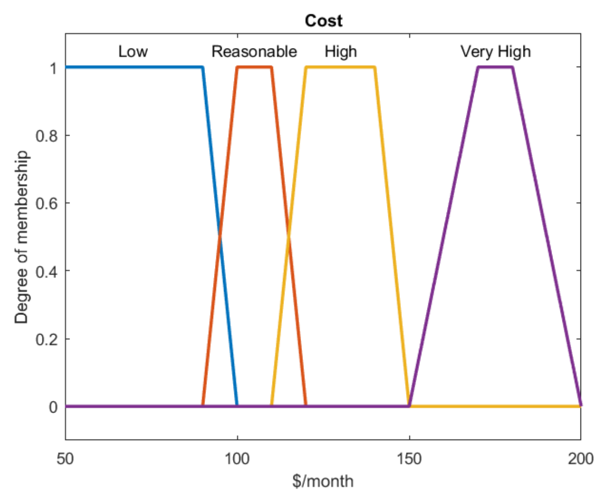

Figure 4. Cost for cloud subscription

3) Performance

The Cloud performance is calculated using the CPU and database performance scores. The cloud service provider's database performance is the performance parameter. Table 5 shows the linguistics and respective crisp values using similar trapezoidal MF.

TABLE V. Membership of Performance

No.	Linguistic Term	Values(Performance Score)
1	Poor	[10, 20, 30 ,40]
2	Satisfactory	[30 , 40, 50, 60]
3	Good	[50, 60 ,70 ,80]
4	Excellent	[80, 85, 90 ,100]

The universe of discourse(U) is set to 100 in order to show the database performance on a scale of 0 to 100 (0-100 percent). Fig. 5 represents the graph of the membership function ‘performance’.

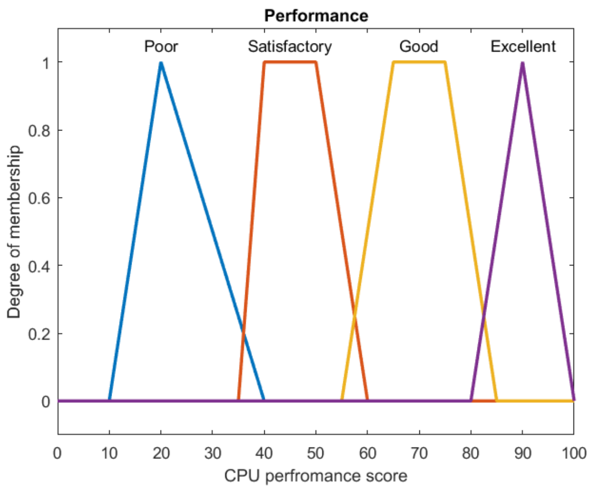

Figure 5. Database Performance Score

4) Security

Security is a key concern for cloud users since their data is kept in a remote place. Having security issues in a cloud system might cause huge losses for both parties. Different CSPs offer different security levels, such as level-1 and level-2. It is necessary to have a strong SLA between the CSP and the end-user. The average cloud system strength of the provider is the statistic used to measure security.

Fig. 6 represents the fuzzy graph of the membership function ‘security.’

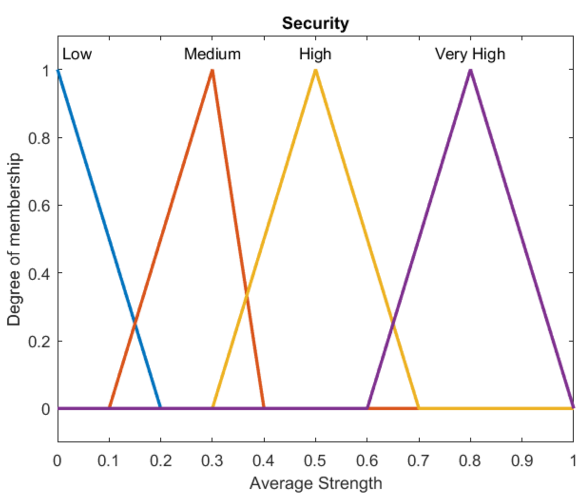

Figure 6. Strength of security

Table 6 shows the linguistic terms and corresponding fuzzy values, which are articulated more accurately using the triangular MF.

TABLE VI. Membership for security in the cloud

No.	Linguistic Term	Values (Levels)
1	Very High	[0.6, 0.8, 1]
2	High	[0.3, 0.5, 0.7]
3	Medium	[0.1, 0.3, 0.4]
4	Low	[-0.1, 0, 0.2]

5) Maintenance

Cloud services need regular system maintenance. We compared the maintenance service provider’s uptime and free support. Up-time is the amount of time that the cloud remains operational during maintenance. For example, if the cloud offers free assistance with a bought subscription, it will be labeled as (0 or 1).

Table 7 shows the linguistic words and their precise input values using the trapezoidal MF. The universe of discourse (U) is set to 100, which indicates the system’s maximum uptime(in %) during maintenance.

TABLE VII. Membership for Maintenance

No.	Linguistic Term	Values(%)
1	Poor	[0 , 15 , 20, 30]
2	Satisfactory	[25 , 35 ,45 ,60]
3	Good	[55 , 65 ,75 ,85]
4	Excellent	[80, 90 , 95, 100]

Fig. 7 represents the fuzzy graph of the membership function ‘maintenance.’

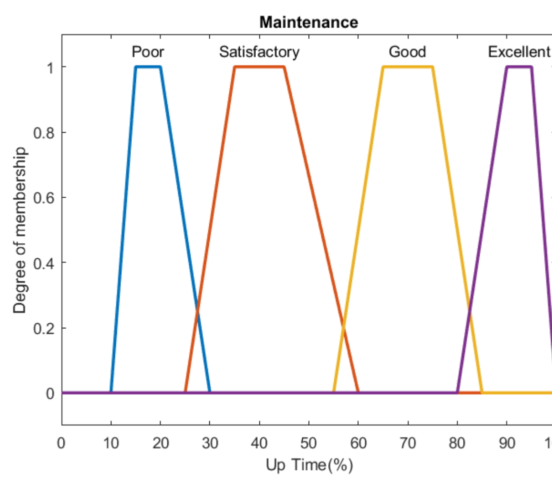

Figure 7. Cloud Up-time during maintenance (%)

Phase 2- Construct a Fuzzy rule base and define the fuzzy algorithm

Step 1: Construct a Fuzzy rule base

In this phase, a Fuzzy rule base is built to handle the proposed model's flow control by converting the given crisp values into corresponding fuzzy values and then deducing fuzzy rules. In order to govern the flow of data, fuzzy logic creates a set of rules. (IF-THEN-ELSE) to reduce uncertainty in trust-based QoS models like pattern classification and decision making. A domain expert knowledge is required for the creation of a rule base [cite]. The various literature and detailed study of existing models enabled us to create the FIS of the fuzzy rule base. The defined rules in the Fuzzy Inference System (FIS) of the proposed and the proposed algorithm of the MC-DMFT model are as follows:

Fuzzy Inference Rules:

R: Reasonable, G:Good, E: Extensive, P:Poor, S:Satisfactory, Excellent, L: Low, M: Medium, H: High, VL: VeryLow, VH: VeryHigh.

1) IF C_p is R $\wedge$ P_f is L $\wedge$ C_o is H $\wedge$ S_e is M $\wedge$ M_t is S THEN the Rank is 'M'.
2) IF C_p is R $\wedge$ P_f is H $\wedge$ C_o is R $\wedge$ S_e is M $\wedge$ M_t is H , THEN the Rank is 'H'.
3) IF C_p is E $\wedge$ P_f is H $\wedge$ C_o is L $\wedge$ S_e is H $\wedge$ M_t is H THEN the Rank is 'VH'.
4) IF C_p is E $\wedge$ C_o is R $\wedge$ P_f is H $\wedge$ S_e is M $\wedge$ M_t is G, THEN the Rank is 'H'.
5) IF C_p is E $\wedge$ P_f is S $\wedge$ C_o is R $\wedge$ S_e is M $\wedge$ M_t is H, THEN the Rank is 'H'.
6) IF C_p is G $\wedge$ C_o is H $\wedge$ P_f is E $\wedge$ S_e is H $\wedge$ M_t is G, THEN the Rank is 'H'.
7) IF C_p is G $\wedge$ C_o is H $\wedge$ P_f is P $\wedge$ S_e is L $\wedge$ M_t is P, THEN the Rank is 'L'.

Table 8 shows 27 rules developed in the FIS of the proposed model to acquire the rank of different CSPs utilizing different user criteria.

Here, C_p, C_o, P_f, S_e, and Mt are the input parameters representing capacity, cost, performance, security, and maintenance, respectively.

A pre-defined set of Fuzzy rules is used to choose the membership functions. The FIS rule base also provides the ability to set the priority of the different parameters as per the need of Cloud users. For instance, the priority index for

TABLE VIII. Defined rules of FIS

Rules	Capacity	Cost	Performance	Security	Maintenance	Rank
1	R	L	P	L	P	VL
2	R	L	P	L	S	VL
3	R	L	P	M	G	VL
4	R	L	P	M	E	L
5	R	L	S	H	P	L
6	R	L	S	H	S	M
7	R	R	S	VH	G	H
8	R	R	S	VH	E	H
9	R	R	G	L	P	L
10	G	R	G	L	S	M
11	G	R	G	M	G	H
12	G	R	G	M	E	H
13	G	R	E	H	P	M
14	G	H	E	H	S	H
15	G	H	E	VH	G	H
16	G	H	E	VH	E	H
17	G	H	P	L	P	M
18	G	H	P	L	S	M
19	E	H	P	M	G	M
20	E	VH	P	M	E	M
21	E	VH	S	H	P	M
22	E	VH	S	H	S	H
23	E	VH	S	VH	G	M
24	E	VH	S	VH	E	L
25	E	VH	G	L	P	M
26	E	VH	G	L	S	M
27	E	L	E	VH	E	VH

picking a CSP is shown using Eq. 12 as follows:

$$C_p > P_f > C_o > S_e > M_t \tag{12}$$

Similarly, preferences can be re-arranged from time to time for different users as per their requirements. The selected parameters are used in the proposed multi-criteria dual membership based fuzzy technique as inputs and based on the selected input parameters, a multi-criteria rule based algorithm is proposed to trigger the corresponding rules form rule base of FIS. The pseudo code of the proposed algorithm is as follows:

Algorithm 1 Multi-Criteria Rule base Algorithm

Require: C_1, C_2,..., C_n: Number of Clouds, T_1: Lower Threshold, T_2: Lower Threshold, T_h : Threshold, n : number of selected parameters

Begin

Identifying the input and output variables

Create membership function of each 1,2,3,....n variable along with fuzzy sets

for each Cloud 1 : N

Define the sets of fuzzy rules which relate to input and output variable

Transform crisp values to fuzzy values using the membership function

Membership function

$$MF = \begin{cases} 1 & \text{Input } x \le T1 \\ \frac{(T1-Input)}{(T1-T2)} & T1 < Input < T2 \\ 0 & \text{Input } x \le T2 \end{cases}$$

In the rule base, examine IF-ELSE rules

The outcome of each rule is added together

Transformation of output values to non-fuzzy values

End for

end

Phase 3: De-fuzzification of output using DMFT

Definition: A membership function (MF) for a defined fuzzy set representing the universe of discourse K is represented as μX:K $\rightarrow$ [0,1], where each element of set K is mapped to a value lies between 0 and 1. This numeric value is called membership value or degree of membership that quantifies the range of membership for the element K to the fuzzy set X.

Trapezoidal MF

$$Trap(x : a, b, c, d) = \begin{cases} 0 & \text{if } x \le a \\ \frac{(x-a)}{(b-a)} & \text{if } a \le x \le b \\ 1 & \text{if } b \le x \le c \\ 0 & \text{if } d \le x \end{cases} \tag{13}$$

$$\mu_{\text{trapezoid}} = \max\left(\left(\min \frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right), 0\right) \tag{14}$$

Where 'x' represents the input and 'a' and 'b' represent the upper and lower thresholds, respectively.

Triangular MF

$$\mu_{\text{triangular}}(x) = \begin{cases} 0 \text{ if } & x <= a \\ \frac{x-a}{b-a} \text{ if } a \le x \le b \\ \frac{c-x}{c-b} \text{ if } b \le x \le c \\ 0 \text{ if } x \ge c \end{cases} \tag{15}$$

The membership functions for selected inputs are μA(C_p), μB(C_o) μC(P_f) μD(S_e) and μE(M_t). In addition, each input has an Lower and Upper threshold. TH_1, TH_2, TH_3,..., TH_{10} correspond to the appropriate thresholds. For the model to operate, the input value must be greater or equal to the activation point (lower threshold). Eq. (16-20) are used to calculate the membership function for output as follows:

$$\mu_x(C_p) = \left\{ \begin{array}{ll} 1 & if C_p \le TH_1 \\ TH_1 - C_p/TH_1 - TH_2 & if TH_1 < Cp < TH_2 \\ 0 & if C_p \ge TH_2 \end{array} \right\} \tag{16}$$

$$\mu_y(C_o) = \left\{ \begin{array}{ll} 0 & \text{if } \mathrm{C_o} \le \mathrm{TH_3} \\ \mathrm{C_o} - \mathrm{TH_3}/\mathrm{TH_3} - \mathrm{TH_4} & \text{if } \mathrm{TH_3} < \mathrm{C_o} < \mathrm{TH_4} \\ 1 & \text{if } \mathrm{C_o} \ge \mathrm{TH_4} \end{array} \right\} \tag{17}$$

$$\mu_z(P_f) = \left\{ \begin{array}{cc} 0 & \text{if } \mathrm{P_f} \le \mathrm{TH_5} \\ \mathrm{P_f} - \mathrm{TH_5}/\mathrm{TH_5} - \mathrm{TH_6} & \text{if } \mathrm{TH_5} < \mathrm{P_f} < \mathrm{TH_6} \\ 1 & \text{if } \mathrm{P_f} \ge \mathrm{TH_6} \end{array} \right\} \tag{18}$$

$$\mu_z(M_t) = \left\{ \begin{array}{ll} 0 & \text{if } \mathrm{M_t} \le \mathrm{TH_7} \\ \mathrm{M_t} - \mathrm{TH_7}/\mathrm{TH_7} - \mathrm{TH_8} & \text{if } \mathrm{TH_7} < \mathrm{P_f} < \mathrm{TH_8} \\ 1 & \text{if } \mathrm{P_f} \ge \mathrm{TH_8} \end{array} \right\} \tag{19}$$

$$\mu_z(S_e) = \left\{ \begin{array}{ll} 0 & \text{if } \mathrm{S_e} \le \mathrm{TH_9} \\ \mathrm{S_e} - \mathrm{TH_9}/\mathrm{TH_9} - \mathrm{TH_{10}} & \text{if } \mathrm{TH_9} < \mathrm{P_f} < \mathrm{TH_{10}} \\ 1 & \text{if } \mathrm{P_f} \ge \mathrm{TH_{10}} \end{array} \right\} \tag{20}$$

The output variables containing the Cloud ranking values are represented in Table 9.

TABLE IX. Fuzzy based OMF variables

No.	Linguistic Term	Values (Membership)
1	[0,0,1,2]	VLow
2	[1.5, 2.5, 3, 3.5]	Low
3	[3.2, 4.5, 5, 5.5]	Medium
3	[5.2, 6, 6.5, 7]	High
3	[6.8, 7.5, 9, 10]	VHigh

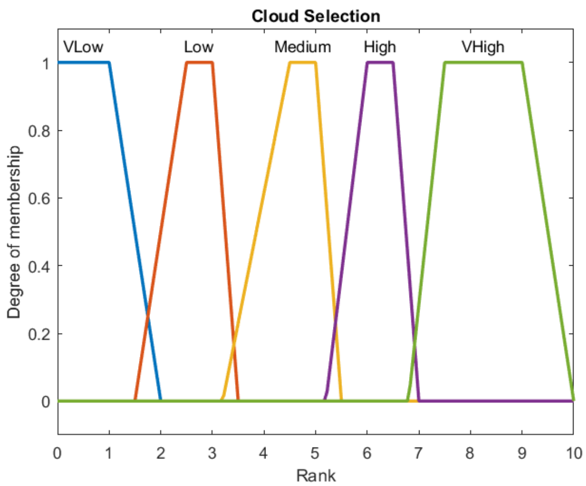

Figure 8. Rank of Cloud

Fig. 8 shows the fuzzy graph for membership of cloud rank.

5. Validation

In the proposed MC-DMFT technique, user preference indexes are collected and considered for the evaluation process to allocate the best suitable cloud and its resources to the users.

Let us consider a system of 5 Cloud users

Now suppose the Priority Index (PI) and the Cloud resource requirements (CRR) for the User1 is as follows:

Priority Index (PI) =

$$C_p > P_f > S_e > M_t > C_o = \{1, 0.8, 0.6, 0.4, 0.2\} \tag{21}$$

Where higher vales represent high precedence.

Cloud resource requirements (CRR) = U1= [Capacity, Cost, Performance, Security, Maintenance]

$$= [36.3, 101, 97, 0.90, 93.4] \tag{22}$$

Now, using the membership functions(MF) presented in Tables 10 and 11, compute the degree of membership of PI and CRR.

TABLE X. Degree of membership of variable 'Precedence Index'

Precedence Index (PI)	Degree of Membership
100	1
80	1
60	0.5
40	0.5
20	0

TABLE XI. Degree of membership of variable 'Cloud Resource Requiremets'

Cloud Resource Requirement (CRR)	Degree of Membership
36.3	1
101	1
97	0.6
0.9	0.5
93.4	0

In Table X, for the PI 1, 0.8, 0.6, 0.4, 0.2, the degree of memberships are 1, 1, 0.5, 0.5, 0, respectively.

In Table XI, for the CRR set 36.3, 101, 97, 0.90, 93.4, the degree of memberships are 1, 1, 0.6, 0.5, 0, respectively.

To find a fuzzy relationship, use the AND (∧) method on the membership value of PI (∧) CRR is shown in Table XII.

TABLE XII. Data Instance of different cloud services providers

CRR/PI	36.3	101	97	0.90	93.4
1	1 ∧ 1	1 ∧ 1	1 ∧ 0.6	1 ∧ 0.5	1 ∧ 0
0.8	1 ∧ 1	1 ∧ 1	1 ∧ 0.6	1 ∧ 0.5	1 ∧ 0
0.6	0.5 ∧ 1	0.5 ∧ 1	0.5 ∧ 0.6	0.5 ∧ 0.5	0.5 ∧ 0
0.4	0.5∧ 1	0.5 ∧ 1	0.5 ∧ 0.6	0.5 ∧ 0.5	0.5 ∧ 0
0.2	0 ∧ 1	0 ∧ 1	0 ∧ 0.6	0 ∧ 0.5	0 ∧ 0

Table XIII shows the results of the AND (∧) operation on the membership values of PI and CRR.

TABLE XIII. Result after AND (∧) fuzzy operation

CRR/PI	36.3	101	97	0.90	93.4
1	1	1	0.6	0.5	0
0.8	1	1	0.6	0.5	0
0.6	0.5	0.5	0.5	0.6	0
0.4	0.5	0.5	0.5	0.5	0
0.2	0	0	0	0	0

Table XIV shows the possible combinations of PI and CRR and their higher membership values.

TABLE XIV. Possible Output

CRR/PI	36.3	101
1	1	1
0.8	1	1

TABLE XV. Output table with the degree of membership

S. No.	PI	Membership function	CRR	Membership function
1	1	Very High	36.3	High
2	0.8	High	36.3	High
3	1	Very High	101	High
4	0.8	High	101	High

The possible resultant combinations of PI and CRR for evaluation of rank value using fuzzy rules as follows:

1) PI-1 = 1 and CRR-1 = 0.8
2) PI-2 = 0.8 and CRR-2 = 0.8
3) PI-3 = 1 and CRR-3 = 0.9
4) PI-4 = 0.8 and CRR-4 = 0.9

6. Simulation

The simulation was carried out using 'Matlab.' The reference data for the cloud selection parameters that are considered in the simulations are obtained using Table 2. The subscription plans of five clouds (C1, C2,......, and C5) are used in the simulation process. The different random users (U1, U2, U3, and U4) are evaluated to determine the rank value of each cloud with respect to users. The 'Mamdani' Fuzzy Inference System (FIS) was used in the simulation since it provides a better simulation representation compared to the 'Sugeno' Fuzzy Inference System (FIS). Fig. 9 depicts the input parameters and output of the proposed model.

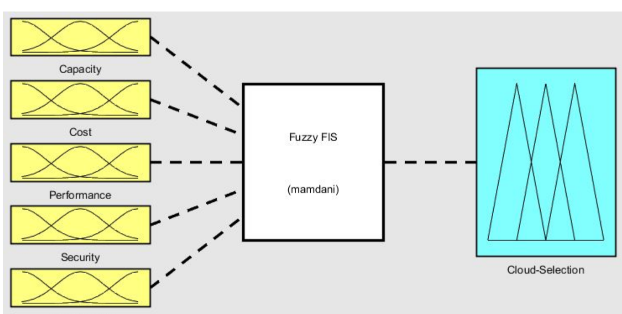

Figure 9. Fuzzy-based rank evaluation model

Given User1's input values as [36.3, 101, 97, 0.90, 93.4], the precedence index (PI) for the various parameters utilized by user U1 is as follows:

$$C_p > P_f > S_e > M_t > C_o$$

The proposed MC-DMFT model computes the rank value for user U1 is computed as 0.82, indicating that U1 has a very high probability of picking the cloud C4. User U1's position in the ranking system is depicted in Fig. 10.

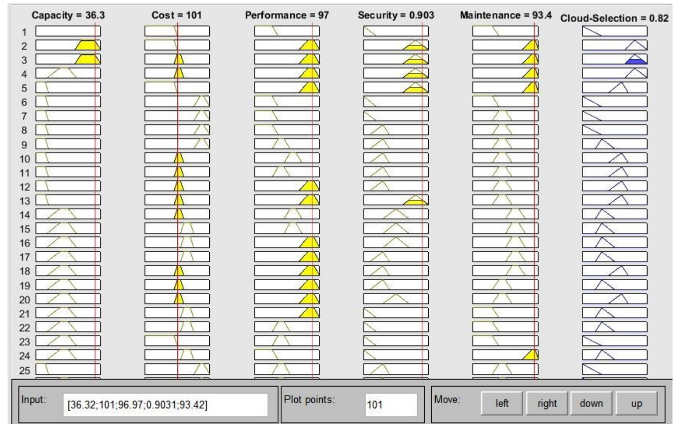

Figure 10. Rank value for User U1

Considering the user input values for U2 as [30.2, 101, 83.2, 0.79, 80.6], and the precedence index (PI) for U2 is:

$$C_0 > P_f > C_p > S_e > M_t$$

The model calculates a rank value as 0.72 for U2, indicating that the cloud user U2 has a high probability of choosing the cloud. Fig. 11 illustrates the rank for U2.

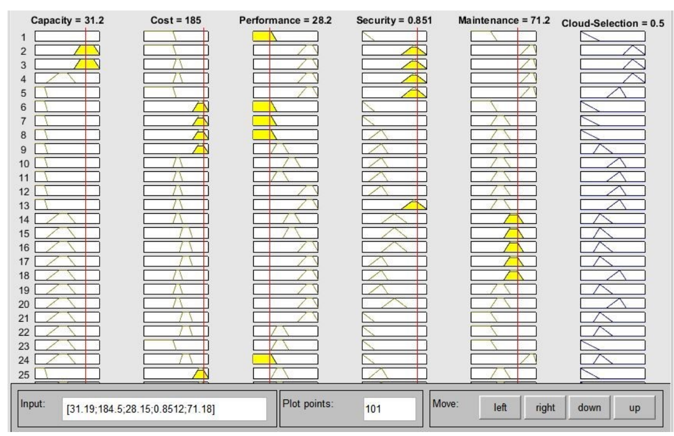

Figure 11. Rank value for User U2

In input vector for U3 is taken as [31.2, 185, 28.2, 0.85, 71.2], and the precedence index (PI) for U3 is:

$$P_f < C_p < C_o < S_e < M_t$$

As a result of the proposed MC-DMFT model, the rank for U3 is calculated as 0.5, which indicates that the cloud User U3 has a moderate possibility of picking the cloud. Fig. 12 depicts the rank for U3. Table 16 shows the ranking of different cloud with respect to different users.

TABLE XVI. Users Priority index and cloud ranking

Sr. No.	Reference User	C1	Rank of Cloud C2	C3	C4	C5	Obtained Priorities of Cloud Service
1.	U1	0.6	0.72	0.78	0.82	0.7	$C4 > C3 > C2 > C5 > C1$
2.	U2	0.48	0.48	0.49	0.5	0.49	$C4 > C3 > C5 > C2 > C1$
3.	U3	0.29	0.45	0.4	0.3	0.38	$C2 > C3 > C5 > C4 > C1$
4.	U4	0.56	0.54	0.7	0.72	0.6	$C4 > C3 > C5 > C1 > C2$

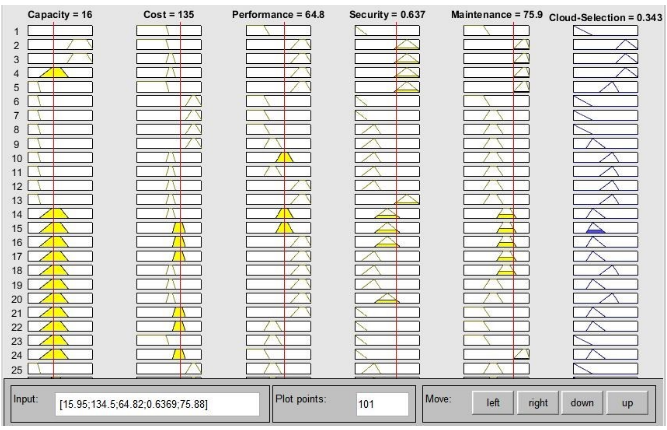

Figure 12. Rank value for User U3

The input vector for user U4 is taken as [16, 135, 64.8, 0.63, 75.9], and he precedence index (PI) for U4 is:

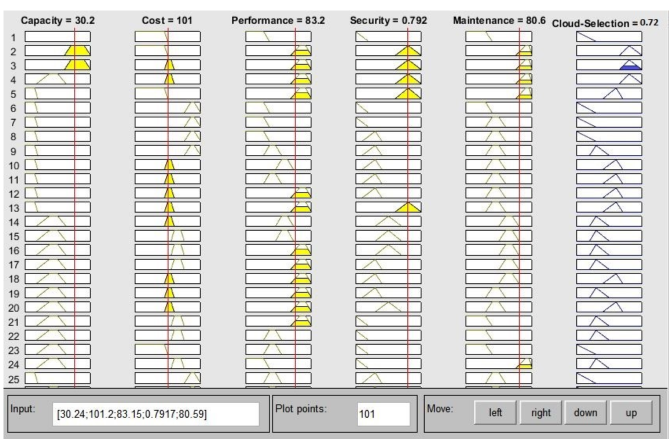

Figure 13. Rank value for User U4

The rank for U4 computed by the model is 0.34, indicating that the cloud User U4 has a low likelihood of picking the cloud. Fig. 13 depicts the rank of U4. Fig. 14 shows the following generic comparison graph of selected attributes for the five clouds and their resource instances.

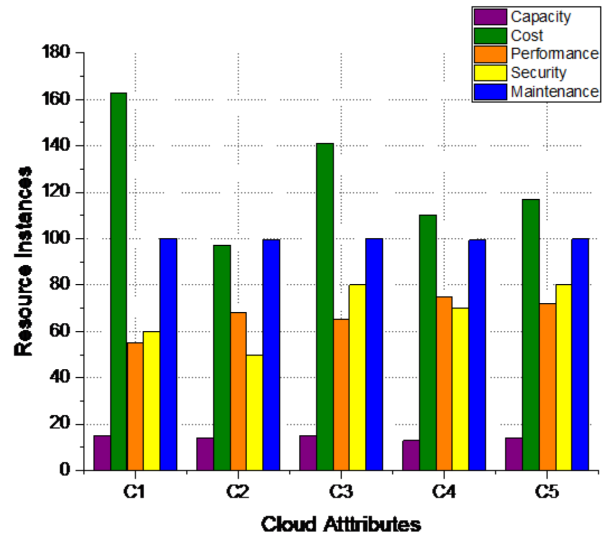

Figure 14. Attribute comparison of different clouds

On the basis of the data obtained in Table II, the suggested model for cloud ranking keeps track of the factors that are taken into account for distinct clouds. In this study, we discovered that providing high-quality service at an affordable price is a significant component in the User 1 decision to choose the Cloud with the highest likelihood of success.

The cloud priority suggestion based on the achieved rank value for U1 is as follows:

$$C4 > C3 > C2 > C5 > C1$$

Fig. 15 shows the distinct priority attributes of users U1, U2, U3, and U4 in terms of their respective priority attributes.

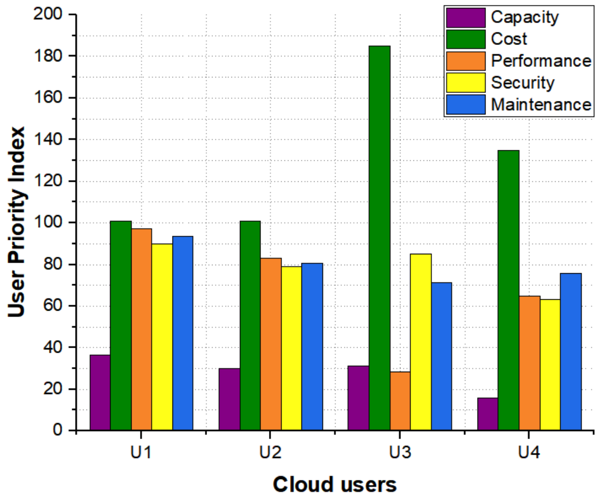

Figure 15. Comparison of user priority attributes

User U2 is likely to pay a higher cost for cloud services in exchange for more memory and performance. Despite the fact that the CSP provides high levels of security and better system maintenance, it suffers from poor performance, which causes the CSP to decline from its high ranking to a moderate ranking.

The following is the cloud recommended priority for User U2 based on the determined rank value is as follows:

$$C1 < C2 < C5 < C3 < C4$$

User U3 pays a higher cost for Cloud services, and the cloud service provider (CSP) provides a moderate QoS in terms of capacity, maintenance, performance, and security. As a result, User U3's ranking drops significantly.

The following is the cloud suggestion priority for User U3 based on the obtained rank value:

$$C1 < C4 < C5 < C3 < C2$$

A similar service is provided by CSP to User 4, who receives an extremely valuable cloud service at a low cost, which places the provider in the high-ranking category.

The following is the cloud recommended precedence for User 4 based on the rank value obtained is as follows:

$$C2 < C1 < C5 < C3 < C4$$

A. Comparative analysis

In the comparative analysis of the proposed MC-DMFT technique, AHP, ANP, and M-TOPSIS techniques are used to ensure that the results of the proposed MC-DMFT technique are consistent and compatible with existing MCDM techniques. In the simulation, the proposed model and the existing models were tested with identical datasets. The proposed model computed the rank values, which were relatively close (showed high relativity) to those of the modified-TOPSIS (M-TOPSIS) approach. A substantial degree of correlation was found between the ranks acquired using the ANP and AHP. The overall comparative analysis during the simulation showed that the proposed approach outperformed ANP and AHP. Fig. 16 depicts the outcome of comparison with existing approaches to acquiring the data for ranking.

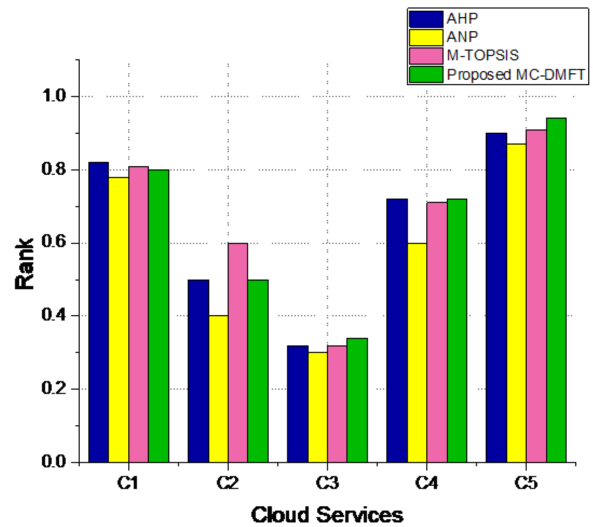

Figure 16. Comparison of performance with AHP, ANP, and M-TOPSIS

7. Conclusions and Future Work

The research work evaluates different cloud services offered by various CSPs and chooses the most suitable cloud service in a fuzzy-enabled environment. The major contribution of the work is that it provides a model-enabled technique that handles the ambiguity in the human decision for the selection of multi-criteria parameters and their relative importance. In this aspect, we have proposed a model that computes the rank and prioritizes various Cloud services with selected selected key parameters. These parameters include capacity, cost, maintenance performance, and security. The simulation was performed for the five clouds using their cloud subscription plan offerings, and four random users were tested for the evaluation of the clouds using the proposed MC-DMFT approach. The model computed the rank value of C_4 as 0.82, which is the highest among all the five clouds for user U1, and it can be subscribed by U1 to get the desired QoS. The proposed model's performance is compared to AHP, ANP, and M-TOPSIS techniques on the same dataset, and the result has shown high relativity. The proposed MC-DMFT model outperforms AHP and ANP and is well correlated with M-TOPSIS. Moreover, the performance achieved in the simulations showed that the proposed approach has been found suitable for complex multi-criteria decision-making problems along with handling the uncertainty in the process of decision-making. There may be some biases that exist due to the involvement of human expert judgments in the fuzzy rule base generation. In the future, multi-level-based hierarchical architecture along with QoS parameters to handle users in dynamic time will be introduced. A large number of users will be tested using a more effective real-time dataset with a wider scope and improved efficiency.

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