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METHODOLOGIES AND APPLICATION

SELCLOUD: a hybrid multi-criteria decision-making model for selection of cloud services

Chandrashekar Jatoth[1,2] · G. R. Gangadharan[2] · Ugo Fiore[3] · Rajkumar Buyya[4]

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Abstract
With the growing demand and commercial availability of cloud services, the need for comparison of their functionality against different prices and performance has arisen. A relevant and fair comparison is still challenging due to diverse deployment options and dissimilar features of different services. This paper addresses a hybrid multi-criteria decision-making model involving the selection of cloud services among the available alternatives. The proposed methodology assigns various ranks to cloud services based on the quantified quality-of-service parameters using a novel extended Grey Technique for Order of Preference by Similarity to Ideal Solution integrated with analytical hierarchical process. Further, we analyse the proposed cloud service selection method in terms of sensitivity analysis, adequacy under change in alternatives, adequacy to support group decision-making, and handling of uncertainty. This analysis helps both researchers and practitioners for analysing more fruitful approaches for cloud service selection.

Keywords Cloud computing · Multi-criteria decision-making · Quality of service · Grey TOPSIS

1 Introduction

Cloud computing has gained enormous popularity in the last few years. It offers undeniable advantages in terms of cost and reliability compared to the traditional computing models, which use a dedicated in-house infrastructure (Buyya et al. 2009). There is a high growth in public cloud computing services providers such as Google, Microsoft, Amazon, GoGrid, and Rackspace. They offer various options in the quality of service (QoS) and pricing of cloud services. The presence of many cloud services raises a question: "How does a cloud service perform better compared to others?" An answer to this question benefits both customers and providers. The answer could help potential customers to choose a service that best fits their performance and cost needs. For instance, they may pick a service for storage intensive applications and another service for computation intensive applications. For cloud service providers, such answer could point them in the right direction for improvement.

Due to the proliferation of cloud services with varying characteristics, it becomes difficult to select an optimal cloud service to fulfil and satisfy user requirements and business strategies, with objectives that sometimes conflict with one another (Cusumano 2010; De Assunção et al. 2010; Chandrashekar et al. 2016; Di Martino et al. 2017; Hajji and Mezni 2017; Capuano et al. 2017a, b; Carrasco et al. 2017). The most suitable cloud service should be sought considering multiple incompatible quantitative and qualitative criteria. Thus, the selection of cloud services can be viewed as a multi-criteria decision-making (MCDM) problem. MCDM usually aims to reveal the best option among all of the feasible alternatives

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✉ G. R. Gangadharan
grgangadharan@idrbt.ac.in

Chandrashekar Jatoth
chandrashekar.jatoth@gmail.com

Ugo Fiore
ugo.fiore@uniparthenope.it

Rajkumar Buyya
rbuyya@unimelb.edu.au

1 School of Computer and Information Sciences, University of Hyderabad, Hyderabad, India

2 Institute for Development and Research in Banking Technology (IDRBT), Hyderabad, India

3 Department of Management and Quantitative Studies, Parthenope University, Naples, Italy

4 Cloud Computing and Distributed Systems (CLOUDS) Laboratory, Department of Computing and Information Systems, The University of Melbourne, Parkville, Australia

in the presence of multiple adverse decision criteria. The aim of MCDM here is to evaluate and rank the alternatives on the QoS and cost parameters.

As there is a growth of popularity in cloud computing, it has been applied in scientific computing and web services selection based on attributes including security, assurance, accountability, performance, and cost. Analytic hierarchy process (AHP) is a MCDM approach in which factors are arranged in a hierarchic structure (Saaty 2001). Tran et al. (2009) developed an AHP-based ranking algorithm for web service selection, considering different QoS attributes of web services using a QoS ontology for obtaining various QoS information and constraints (tendency, mandatory, weighting, relationship, grouping, etc.) of web services. Garg et al. (2013) proposed a Service Measurement Index (SMI) for comparing and ranking cloud services using SMI criteria. The proposed framework computed all the QoS attributes in SMI and used AHP method to rank the cloud services. Godse and Mulik (2009) proposed a method to rank various business functionalities of SaaS services using AHP, considering functionality, architecture, usability, vendor reputation, and cost.

Although AHP is an efficient approach for making decisions, it does not consider the uncertainty of decision in determining pairwise comparison. In this context, fuzzy AHP is introduced to overcome this difficulty, allowing decision makers to use fuzzy ranking in place of exact ranking (Enea and Piazza 2004). Shivakumar et al. (2013) adopted a fuzzy multi-attribute decision-making method for ranking cloud service. In their proposed method, QoS parameters are considered as fuzzy sets and used fuzzy 'and' operator to model the final decision as the intersection of the underlying fuzzy sets. Pernici and Siadat (2011) presented a novel approach using hierarchical fuzzy inference systems for selecting adaptation strategies in service-oriented systems. Bedi et al. (2012) proposed a model for cloud service selection based on a cooperative model of society and handling uncertainty through fuzzy inference system. But, in fuzzy AHP, the decision maker has to give membership value of alternatives which might be within an interval. However, it is often difficult for the expert to precisely quantify her selected number within the interval [0, 1].

Li et al. (2010) developed a framework, namely CloudCmp, that compared various cloud services. CloudCmp measures various services offered by a cloud along metrics that directly reflect their impact on the performance of customer applications. Esposito et al. (2016) proposed a novel approach, in which they applied the fuzzy set theory to set the preferences of the users and Dempster–Shafer theory and game theoretic method to select the services. Zheng et al. (2013) presented a QoS ranking prediction framework to select cloud service by taking benefits of the past cloud service usage experiences of the user. Jatoth et al. (2017) discussed a modified versions of data envelopment analysis and super-efficiency data envelopment analysis for assessing cloud services and their efficiencies and ranking based on user preferences.

The Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) Hwang and Yoon (1981) is an MCDM method used to determine the best alternative, which is defined as the one having the shortest distance from the PIA (positive ideal alternative) and the longest distance from the NIA (negative ideal alternative). TOPSIS method provides greater agility and simplicity than other MCDM models. Further, there is no limitation for the number of alternatives and criteria in TOPSIS. Fuzzy TOPSIS and Grey TOPSIS are the combinations of fuzzy set theory and grey theory to TOPSIS, respectively, used to choose the best alternative in a fuzzy environment. In fuzzy TOPSIS method, there is no concept of rank reversal that helps in updating new ranks when the non-optimal service is entered into the system Lima et al. (2014). A fuzzy TOPSIS method proposed for selecting web services when a group of users has different opinions during evaluation (Lo et al. 2010). Kabir and Hasin (2012) evaluated the major factors for quality of web service from the viewpoint of users and developed a systematic multiple attribute evaluation model using TOPSIS and fuzzy TOPSIS. Saripalli and Pingali (2011) described a fuzzy TOPSIS method for selecting cloud services. They used the wideband Delphi method for evaluating the weights of criteria and a simple additive weight method for ranking the cloud services. Some other researchers are proposed a hybrid MCDM models (Kumar et al. 2017; Sun et al. 2016; Liu et al. 2016) for selecting appropriate cloud services. Although fuzzy TOPSIS used to solve uncertainty problems with imprecise data, it cannot handle discrete data and incomplete information. To overcome this problem, grey theory is an effective approach utilized to solve uncertainty problems with discrete data and incomplete information. Further, grey approach considers the condition of the fuzziness, i.e. it deals flexibly with the fuzziness situation. Some researchers utilized grey approach in various domains such as information technology selection (Oztaysi 2014), subcontract selection (Lin et al. 2008), balanced score card (Sadeghi et al. 2013), and ERP vendor selection (Khan and Faisal 2015).

Despite several researchers illustrating the use of AHP, TOPSIS, fuzzy TOPSIS, and Grey TOPSIS in several web/cloud services related applications, to the best of our knowledge, there is a lack of hybrid multi-criteria decision-making model (combination of AHP and Grey TOPSIS) for cloud service selection. The main objective of this paper is to employ a variant of Grey TOPSIS for several real-world cloud services. In this proposed model, AHP method is utilized to assess the weight of each criteria, Grey TOPSIS is used to assess and ranking the cloud services. In order to evaluate cloud services, we analyse the QoS parameters that can be found from cloud service providers and benchmarking providers. The proliferation of cloud services with varying functionalities and QoS characteristics could cause causes uncertainty in selecting a cloud service by a user. Further, the missing information about certain QoS parameters may cause uncertainties in selecting cloud services. Our proposal of TOPSIS with grey theory resolves these uncertainties in the selection process of cloud services.

The salient contributions of this paper are summarized as follows:

- A hybrid multi-criteria decision-making framework (extended Grey TOPSIS using AHP) has been proposed for ranking the cloud services based on their QoS parameters.
- A comprehensive comparison of sensitivity analysis, adequacy under change in alternative, adequacy to support group decision- making, and handling of uncertainty of the proposed three methods, to ascertain preferable cloud services.

This paper aims to provide a systematic method for selecting the best cloud service among the available services for a service consumer. To the best of our knowledge, this is the first research study to select and compare cloud services using extended versions of Grey TOPSIS. The sensitivity analysis applied to these three methods evaluates that the proposed extended versions of Grey TOPSIS provide a robust result. In our study, AHP is integrated with Grey TOPSIS in order to produce a more effective performance decision-making approaches overcoming the uncertainty in data and ambiguity in decision-making.

The remainder of this paper is organized as follows. A motivating scenario describing the complexities of selection of cloud services is described in Sect. 2. In Sect. 3, we outline the concepts of grey theory, Grey TOPSIS, and AHP. The proposed framework is presented 4. The multi-criteria decision-making algorithm for cloud service selection using extended versions of Grey TOPSIS is presented in Sect. 5. A case illustration of our proposed algorithm for cloud service selection is presented in Sect. 6. An analysis of the extended Grey TOPSIS considering sensitivity, effectiveness, adequacy, and uncertainty handling is illustrated in Sect. 7 followed by concluding remarks in Sect. 8.

2 Motivating scenario

Suppose that an imaginary large-sized organization, XYZ, is planning to implement flexible and innovative customer-centric services to improve its efficiency and attract customers. The institution offers various services to customers besides core services, e.g. payment services and customer relationship services like Messaging services, and the like. In order to provide these services with high efficiency and low maintenance cost, XYZ plans to use cloud services, considering the following reasons:

- Cost reduction: The maintenance cost of dedicated hardware, software, and related manpower in XYZ will be highly reduced by using cloud services.
- Improvement in flexibility and scalability: cloud services enable XYZ to respond faster to changing market conditions by dynamically scaling up and down on demand.
- Increased openness to innovation: Testing and integrating new technologies and applications is much easier in cloud.
- Better customer relationships: Cloud combined with big data analytics enables XYZ to better identify trends in customer needs and make its services more tailored.

For implementing its services, XYZ looks for an infrastructure-as-a-service (IaaS) cloud service provider. In today's market, there are many IaaS providers such as Amazon, HP, Microsoft, and Rackspace. Each IaaS provider offers several services varying in QoS attributes with possibly different numbers of virtual cores and memory size. In order to select a service among the available ones, XYZ considers the typically comparable QoS attributes of the services and analyses them.

XYZ considers five QoS parameters: price, processing performance, I/O operational consistency, disc storage performance, and memory performance (See Table 1 for the definitions of these QoS parameters). Table 2 lists sample values of these parameters for four available services (A_1, A_2, A_3, A_4).

Now, XYZ has to choose one service from the available services. This selection is done by comparing all QoS attributes and analysing the performance of each service. The service having the best performance score will be selected.

In general, any institution will tend to select a cloud service that has faster computing and memory operations and has less maintenance cost. The selection process of a service provider will depend on the specific requirements of the institution, which may assign different priorities to the various parameters. If a weight is assigned to each QoS attribute, XYZ can express and change its preferences by manipulating the weights. For example, let us consider three cases in which XYZ changes its priorities (or weights). In case 1, XYZ gives higher priority to processing performance than to the other attributes by assigning weights such as processing performance, 0.4; I/O operational consistency, 0.1; memory performance, 0.2; cost, 0.3; and disc storage performance, 0.1. In this case, the service with high processing performance, i.e. A_3, is selected. In case 2, XYZ prefers a service with low cost and changes the weights accordingly: processing performance, 0.1; I/O operational consistency, 0.1; memory performance, 0.1; cost, 0.6; and disc storage perfor-

Table 1 List of QoS parameters and their description

S. no	QoS attributes	Description
1	Price per hour	The cost of a virtual machine per hour
2	Processsing Performance	The number of jobs that a computer can execute in a given time interval (the processing and orchestration of all applications as integer and FLOPS)
3	I/O operational consistency	The average time required for disc I/O operations to remain consistent (measured in I/O operations/s)
4	Disc storage performance	The number of operations performed on a disc in a certain amount of time (measured in I/O operations/s)
5	Memory performance	The relationship between speed and latency

mance, 0.1. In this case, the high priority is cost, and the cloud service with low cost is selected, i.e. cloud service A_1. In case 3, XYZ prefers efficient disc storage operations. It assigns the weights as processing performance, 0.1; disc storage performance, 0.5; I/O operational consistency, 0.3; price, 0.1; and memory performance, 0.1, giving more importance to high disc storage performance. In this case, A_1 is selected. This type of selection process can be complicated as these changes can result in large variations given a set of cloud services with varying QoS parameters. Hence in order to overcome such problems, our proposed methods are considered for selecting a cloud service to fulfil the requirements of the XYZ organization.

3 Preliminaries

This section presents the essential ideas of grey theory, Grey Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Analytical Hierarchical Process (AHP).

3.1 Grey theory

Grey theory was proposed by Deng (1982, 1988) to cope with uncertainty in problems with small samples and incomplete information. Its emphasis is on constructing models starting from small amounts of observed data. A grey number is an indeterminate number that takes value within an interval. It is denoted as $\otimes x \in [\underline{x}, \overline{x}]$, where $\underline{x}$ is a lower limit real number, and $\overline{x}$ is an upper limit real number for the grey number $\otimes x$. If both its limits are unknown, the number is called a black number (nothing is known). If both upper and lower limits are equal, then it is called a white number (complete information is available).

The basic operations for the grey numbers $\otimes x \in [\underline{x}, \overline{x}]$ and $\otimes y \in [\underline{y}, \overline{y}]$ are defined in (Wang and Wu 1998):

$$\begin{aligned}
(\oplus x + \oplus y) &\in [\underline{x} + \underline{y}, \overline{x} + \overline{y}] \\
(- \oplus x) &\in [-\overline{x}, -\underline{x}\,] \\
(\oplus x \times \oplus y) &\in [\min\{\underline{x}\underline{y},\ \underline{x}\overline{y},\ \overline{x}\underline{y},\ \overline{x}\overline{y}\}, \max\{\underline{x}\underline{y},\ \underline{x}\overline{y},\ \overline{x}\underline{y},\ \overline{x}\overline{y}\}] \\
(1/\oplus x) &\in [1/\overline{x}, 1/\underline{x}\,]
\end{aligned} \tag{1}$$

The multiplication of a grey number by a scalar is done in accordance with

$$(h \oplus x) \in [h\underline{x}, h\overline{x}] \tag{2}$$

where h is a positive real number.

3.2 Grey TOPSIS

Grey TOPSIS is a combination of grey theory and TOPSIS method. The procedural steps of Grey TOPSIS for calculating the criteria weights are demonstrated as follows (Li et al. 2007; Lin et al. 2008):

Step 1: Determine the grey decision matrix D.

Table 2 The sample QoS parameter values for XYZ organization

Service	Virtual core	Price (dollar/h)	Processing performance (FLOPS)	I/O operational consistency (operations/s)	Disc performance (operations/s)	Memory performance (operations/s)
A_1	2	55	75	80	90	85
A_2	4	60	60	85	80	90
A_3	4	80	80	65	85	75
A_4	2	90	60	90	70	75

$$D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccccc} C_1 & C_2 & C_3 & \dots & C_n \end{array} \\ \begin{pmatrix} \otimes x_{11} & \otimes x_{12} & \otimes x_{13} & \dots & \otimes x_{1n} \\ \otimes x_{21} & \otimes x_{22} & \otimes x_{23} & \dots & \otimes x_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \otimes x_{m1} & \otimes x_{m2} & \otimes x_{m3} & \dots & \otimes x_{mn} \end{pmatrix} \end{array} \tag{3}$$

where $\otimes x_{ij}$ denotes the evaluation of grey numbers of the i-th alternative with respect to the i-th criteria. A_i $(A_1, A_2, \dots, A_m)$ represents the m alternatives and $C_j (C_1, C_2, \dots, C_n)$ represents the n criteria.

Step 2: Calculate the criteria weights w_j using Table 4.

Step 3: Normalize the grey decision matrix according to Eq. (4) (Oztaysi 2014).

$$\otimes r_{ij} = \begin{cases} \dfrac{\otimes x_{ij}}{\max\limits_i \overline{x}_{ij}} & \text{for the benefit criteria} \\ 1 - \dfrac{\otimes x_{ij}}{\min\limits_i \underline{x}_{ij}} & \text{for the cost criteria} \end{cases} \tag{4}$$

Step 4: Identify the positive and negative ideal alternatives. The positive ideal alternative A^* and negative ideal alternative A^- are defined as follows.

$$A^* = \{r_1^*, \dots, r_m^*\} \text{ and } A^- = \{r_1^-, \dots, r_m^-\} \tag{5}$$

where

$$r_j^* = \begin{cases} \max\limits_i \overline{r}_{ij} & \text{for the benefit criteria} \\ \min\limits_i \underline{r}_{ij} & \text{for the cost criteria} \end{cases} \tag{6}$$

and

$$r_j^- = \begin{cases} \min\limits_i \underline{r}_{ij} & \text{for the benefit criteria} \\ \max\limits_i \overline{r}_{ij} & \text{for the cost criteria} \end{cases} \tag{7}$$

Step 5: Determine the separation measure of positive (d^*) and negative ideal (d^-) alternatives according to Eqs. (8) and (9) (Lin et al. 2008)

$$d_i^* = \sqrt{\frac{1}{2} \sum_{j=1}^{n} w_i \left((r_j^* - \underline{r}_{ij})^2 + (r_j^* - \overline{r}_{ij})^2 \right)} \tag{8}$$

$$d_i^- = \sqrt{\frac{1}{2} \sum_{j=1}^{n} w_i \left((r_j^- - \underline{r}_{ij})^2 + (r_j^- - \overline{r}_{ij})^2 \right)} \tag{9}$$

Step 6: Calculate the relative closeness (C_i^*) to the positive ideal alternatives.

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

The larger indexed value is considered as the better alternative.

3.3 Analytical hierarchical process (AHP)

AHP is a multi-criteria decision-making model to allow a decision makers to compute a ratio scale from preferences and model a complex problem in a hierarchical structure. This structure based on three steps: goal, criteria (QoS parameters), and alternatives (Saaty 1980). In AHP, at top level the criteria are assessed, and at bottom level the alternatives are evaluated for each criterion. The decision makers evaluated her evaluation separately at each level. The decision makers should calculate the weights of all criteria in order to do pairwise comparison among them. The AHP method is described as follows (Saaty 1988):

1. The problem structure decompose into structural hierarchy (goal, criteria, sub-criteria, and alternatives) (as shown in Fig. 3)
2. Establish the pairwise comparison matrix at each level of structural hierarchy based on priority of input data (the pairwise comparison calculated according to the scale from 1 to 9).
3. Compute vector of weights by using eigenvector procedure.
4. Compute the consistency ratio (CR) to check the consistency of the judgement. If CR < 0.1 then the pairwise comparison is consistent and acceptable. The consistency index (CI) and consistency ratio (CR) of the pairwise comparison matrix A are computed using Eqs. 11 and 12.

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{11}$$

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} \tag{12}$$

where CI is the consistency index, n is the order of the pairwise comparison matrix A, and $\lambda_{\max}$ is its maximum eigenvalue, while the random index RI is the average CI value for random matrices.

4 *SELCLOUD:* a proposed framework for cloud service selection

Our cloud service selection framework *SELCLOUD* is illustrated in Fig. 1. This framework presents the certain facilities like service selection and their ranking by considering functional requirement and non-functional requirements. It provides an output as sorted order cloud services with respect

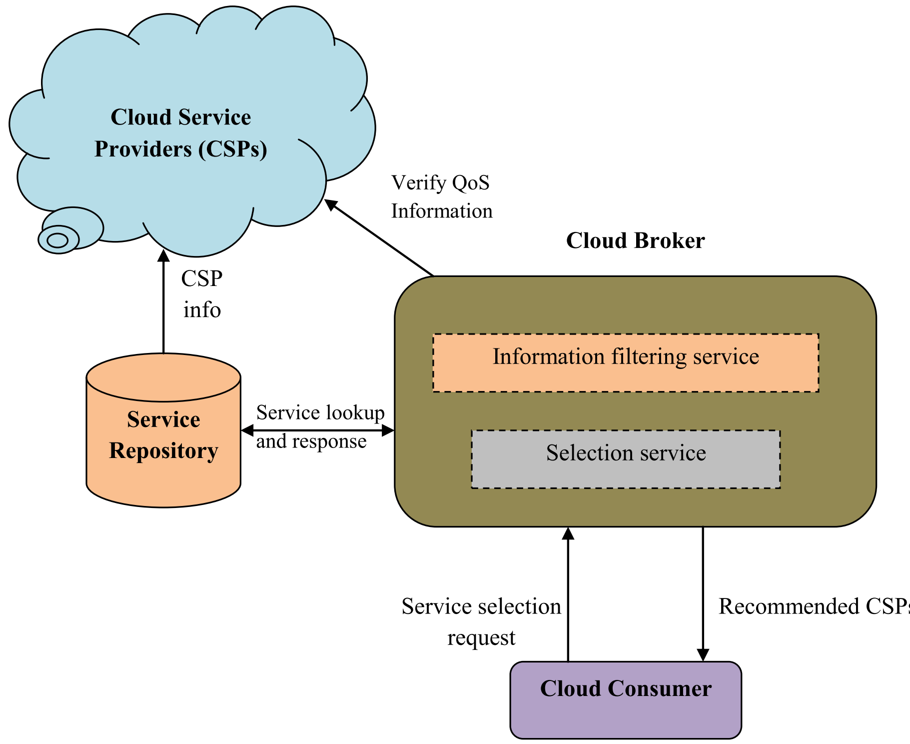


Fig. 1 *SELCLOUD* framework for the cloud service selection

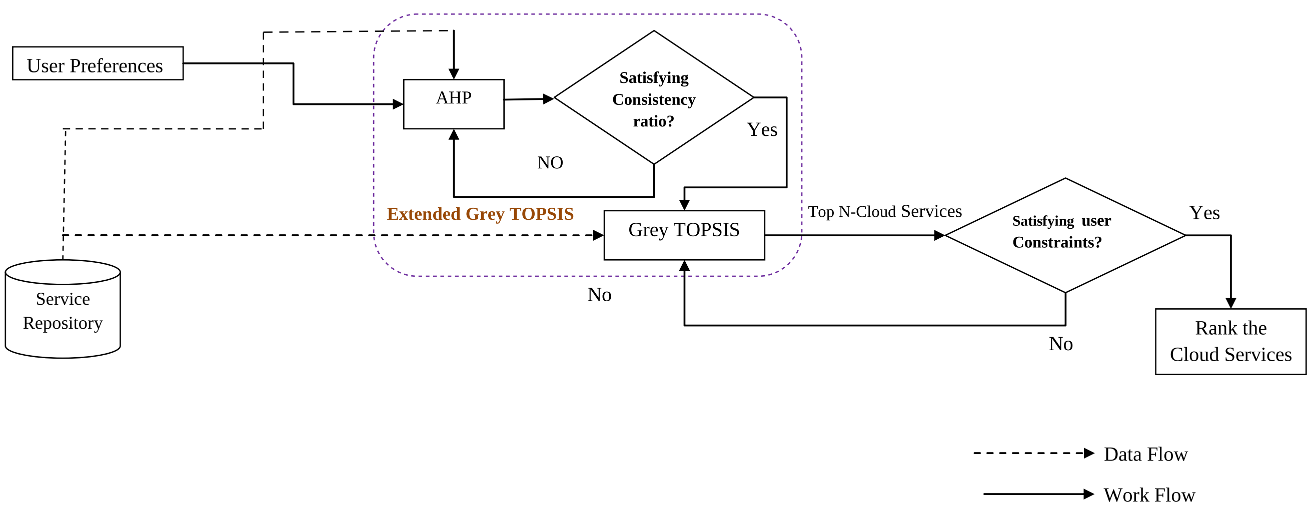


Fig. 2 Data flow and workflow for cloud service selection

to user preferences. This framework consists of four entities: (i) Cloud consumer (user), (ii) Cloud broker, (iii) Cloud service repository, and (iv) Cloud service providers.

Cloud consumer (user) The *cloud consumer* gives her requirements to the *cloud broker* to select the cloud service Providers (CSPs).

Cloud broker The *cloud broker service* serves as a middleman in between the CSPs and cloud consumers. This entity directly interacts with cloud consumers and perceive their functional and non-functional requirements (such as processing performance, I/O operational consistency, disc storage performance, memory performance, price, disc size, number of virtual core, and number of virtual machines). Suppose a *cloud consumer* was looking for a particular cloud service and submits her desired service requirements to the *cloud broker*. Then, the *cloud broker* searches its database and discover most appropriate CSP that satisfying the needs of the consumers. This entity comprises of two important components, i.e. *information filtering* service and *selection* service. The major work of *information filtering* service is filter out the cloud services that do not fulfil the requirement of the consumers and gives the potential CSP satisfying the require-

Table 3 The collected cloud service data set

Providers	Service	Price/Hr(Cents)	Virtual core	Memory	Processing performance	I/O operational consistency	Disc storage performance	Memory performance
C_1	C_1S_1	28	4	15	25.86	92.89	110.33	129.03
	C_1S_2	56	8	30	48.23	53.28	67.22	131.79
C_2	C_2S_1	14	2	7.5	13.89	114.44	97.38	144.86
	C_2S_2	28	4	15	23.66	119.63	100.55	131.81
	C_2S_3	56	8	30	51.7	77.46	73.44	125.59
C_3	C_3S_1	16	4	4	7.21	70.29	125.48	54.28
	C_3S_2	32	8	8	15.33	57.11	111.18	55.68
C_4	C_4S_1	18	2	3.5	8.83	67.87	83.73	52.27
	C_4S_2	36	4	7	16.07	67.97	78.49	61.8
	C_4S_3	72	8	14	28.4	78.72	70.91	27.33
C_5	C_5S_1	12	2	4	16.41	23.43	40.23	80.67
	C_5S_2	45	4	15	32.4	29.07	42.47	90.83
	C_5S_3	90	8	30	52.82	35.35	55.07	83.92
C_6	C_6S_1	8	2	4	17.34	43.02	141.23	51.71
	C_6S_2	16	4	8	37.05	36.15	102.74	132.87
	C_6S_3	32	8	16	71.11	39.66	99.15	135.88
C_7	C_7S_1	10.132	2	4	23.43	89.31	173.49	89.84
	C_7S_2	20.8624	4	8	42.05	59.63	174.5	97.16
	C_7S_3	34.6528	8	16	75.89	64.64	174.12	100.14

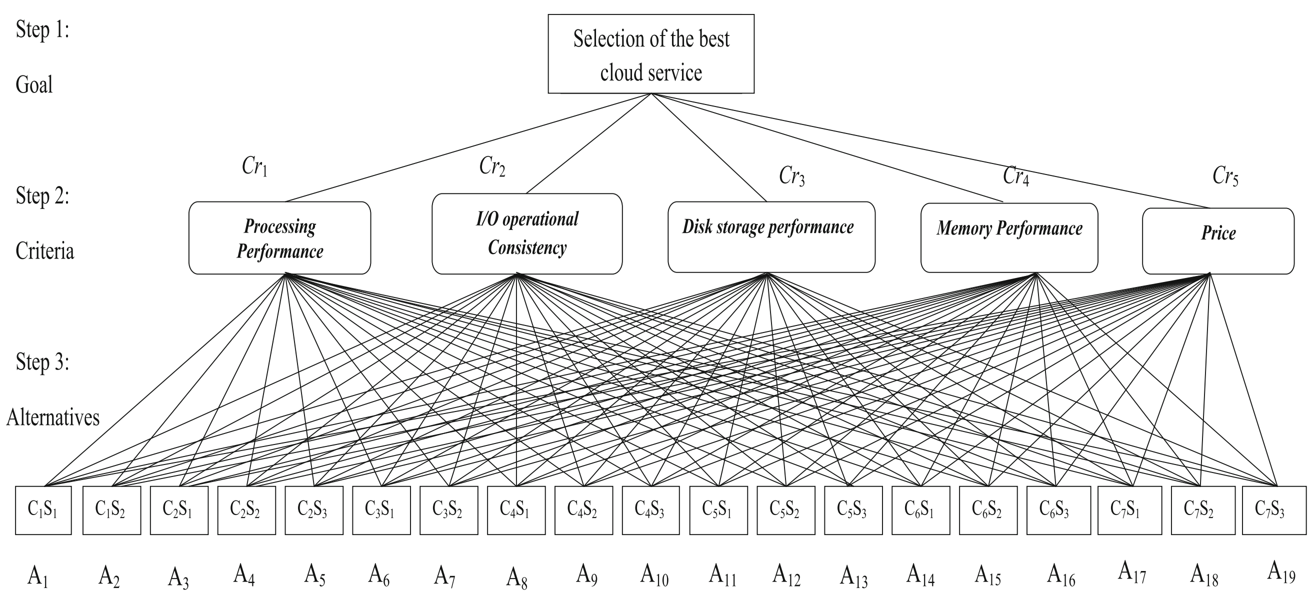


Fig. 3 The hierarchy structure of the cloud service selection

ment of the consumers. The *selection* service evaluates all the qualitative and quantitative parameters (like price, I/O operational consistency, processing performance, memory performance, and number of virtual core). Based on users requirements, the *cloud broker* interacts with service repository and retrieves the related information of CSP. Afterwards, this gathered information is employed by *selection* service (as described in Sect. 5), and it presents the appropriate CSP that satisfies the consumer's requirements.

Cloud service repository This entity stores the detailed information about cloud service providers such as assets, artefacts, and functional and non-functional specifications along with service- level agreements (SLAs). This entity is

Table 4 Scales for comparison matrix

Intensity of importance	Definition
1	Equal Importance
3	Moderate Importance of one over another
5	Essential or Strong Importance
7	Very Strong Importance
9	Extreme Importance
2,4,6,8	Intermediate value between the two adjacent judgements

Table 5 Priority weights

	Cr_1	Cr_2	Cr_3	Cr_4	Cr_5	Weight vector
Cr_1	1	2	3	2	3	0.34523
Cr_2	0.50	1	5	4	2	0.28998
Cr_3	0.33	0.20	1	0.50	0.33	0.068046
Cr_4	0.50	0.25	2	1	0.25	0.10381
Cr_5	0.33	0.50	3	4	1	0.192931

Table 6 Scale of criteria rating

Scale		Grey number
Cr_1	Cr_2 Cr_3 Cr_4 Cr_5	
Very height (VH)	Very Poor (VP)	[1, 2]
Height (H)	Poor (P)	[2, 3]
Medium height (MH)	Medium Poor (MP)	[3, 4]
Medium (M)	Fair (F)	[4, 5]
Medium low (ML)	Medium Good (MG)	[5, 6]
Low (L)	Good (G)	[6, 7]
Very low (VL)	Very Good (VG)	[7, 8]

used by the cloud broker while searching for appropriate CSPs.

Cloud service providers This entity performs continuous analysis of the QoS parameters for cloud services (such as memory performance, disc storage performance, disc I/O operational consistency, processing performance, price, availability, response time, and scalability) using different testing operations. These operations carried out by a trusted third party vendor. In our proposed framework, we used CloudHarmony[1] as the benchmark cloud service provider. The job of this provider is to provide all information of QoS parameters (or attributes) in a quantified form of cloud services by iterating through different operations dynamically and lunching the multiple evaluated instances in a particular time interval, and this QoS information is available for public use.

[1] https://cloudharmony.com.

5 EGTOPSIS: a hybrid multi-criteria decision-making algorithm for cloud service selection

Our *SELCLOUD* framework includes the entity *selection* service that employs a novel extended Grey TOPSIS (EGTOPSIS) algorithm as a combination of Grey TOPSIS with AHP. Generally, the fuzzy approach cannot handle incomplete data and information, though it is adequate for dealing with uncertain and imprecise data. There is no concept of rank reversal in TOPSIS and fuzzy TOPSIS, which can help in updating the ranks when a non-optimal service is entered into the system (Lima et al. 2014), Our proposed EGTOPSIS algorithm can deal with both the fuzziness situation and incomplete information and also incorporates the rank reversal concept.

With MCDM techniques, decision makers have the prospect to explore and combine different aspects of the problem in accordance with their requirements. The main objective of this paper is to select the best alternative from amidst a wide offering of cloud services with respect to complex user preferences. Hence, we use analytical hierarchy process (AHP) to define the priorities of different criteria of QoS parameters of cloud services. Then, we combine AHP with Grey TOPSIS for selecting and ranking the best cloud service. The data flow and workflow for cloud service selection using our proposed approach is shown in Fig. 2.

Initially, we initialize the suitable alternatives and criteria with respect to QoS parameters of cloud services. Subsequently, we select the suitable linguistic variables and ratings for cloud services (as determined by experts). Afterwards, we calculate the criterion weights by using AHP and determine the alternatives with respect to the criteria for cloud services. If the criteria weights are inconsistent, then AHP is used to determine them. The criteria weights are applied to Grey TOPSIS model to evaluate the cloud services.

We establish a *grey decision matrix D* for cloud services (see Eq. 3) based on the criteria with each row representing an alternative and each column representing a criterion. After this process, we calculate the normalized grey decision matrix and the weighted grey decision matrix of cloud services (based on Eqs. 13 and 14). Afterwards, we compute the positive ideal alternative (A^*) and the negative ideal alternative (A^-) for the cloud services and quantify the A^* and A^* of each cloud service by using Eqs. 15 and 16. Following that, we determine the separation measure of the positive ideal alternative (d^*) and that of the negative ideal alternative (d^-) according to Eqs. 17 and 18. After evaluating top n services, these services are checked whether they satisfy user constraints or not. If these services satisfy user constraints, then services are ranked according to their scores; otherwise, the process is repeated until the constraints of the user are satisfied. The pseudocode for EGTOPSIS using AHP is shown in Algorithm 1.

Algorithm 1 Pseudocode representation of EGTOPSIS with AHP

```
Input: Alternatives (a_i j), N: QoS parameters.
Output: Best M.
while M ≠ NULL do
    Construct the Grey Decision matrix D;                ▷ Based on equation 3
    for each x_ij in D do
```

$$\otimes r_{ij} = \left(\frac{\underline{x}_{ij}}{max(\overline{x}_{ij})}; \frac{\overline{x}_{ij}}{max(\underline{x}_{ij})} \right) \tag{13}$$

$$\otimes r_{ij} = \left(1 - \frac{\underline{x}_{ij}}{max(\overline{x}_{ij})}; 1 - \frac{\overline{x}_{ij}}{max(\underline{x}_{ij})} \right) \tag{14}$$

where $\underline{x}_{ij}$ represents the lower limit value and $\overline{x}_{ij}$ represents the upper limit value. ▷ Compute the normalized grey decision matrix ($\otimes r_{ij}$).

$$A^* = \{(max(\overline{r}_{ij}) | j \in J), (min(\underline{r}_{ij}) | j \in J')\} \quad (benefit \quad criteria) \tag{15}$$

and

$$A^- = \{(min(\underline{r}_{ij}) | j \in J), (max(\overline{r}_{ij}) | j \in J')\} \quad (cost \quad criteria) \tag{16}$$

```
        if j ∈ J then
            A* = max(r_ij); A⁻ = min(r_ij)
        else if j ∈ J then
            A* = min(r_ij); A⁻ = max(r_ij)
        end if
    end for
    for J ∈ j ∈ C_j do
```

$$d_i^* = \sqrt{\frac{1}{2} \sum_{j=1}^{n} w_i \left[|r_j^* - \underline{r}_{ij}|^2 + |r_j^* - \overline{r}_{ij}|^2 \right]} \tag{17}$$

$$d_i^- = \sqrt{\frac{1}{2} \sum_{j=1}^{n} w_i \left[|r_j^- - \underline{r}_{ij}|^2 + |r_j^- - \overline{r}_{ij}|^2 \right]} \tag{18}$$

```
    end for          ▷ Compute the separation measure of positive (d+) and negative ideal (d−) alternatives, where w_i represents each criteria weights obtained by AHP method.
    for each x_ij in D do
```

$$C_i^* = \frac{d_i^-}{d_i^* + d_i^-} \tag{19}$$

```
    end for          ▷ Calculate the relative closeness (C_i*) to the positive ideal alternatives.
    Rank the alternatives based on C_i*;    ▷ The larger indexed value is considered as the better alternative.
end while
```

6 Case illustration

We considered seven real-world infrastructure-as-a-service (IaaS) cloud service providers: Amazon, Azure, CenturyLink, City Cloud, Google, HP, and Rackspace (not in any order). These cloud service providers offer two or three cloud services that vary in the number of virtual cores. We classified these cloud services into three categories: *Large* (two virtual cores), *Extra-large* (four virtual cores), and *2x-extra-large* (eight virtual cores). An overview of the data set used in our experiments is presented in Table 3. The cloud services ($C_1S_1, \ldots, C_7S_3$) were encoded as alternatives A_1 to A_{19} (in the same order). The QoS parameters including price, processing performance, I/O operational consistency, disc storage performance, and memory performance of each cloud service were encoded as criteria Cr_1 to Cr_5. The evaluation of the potential cloud services on each criterion was made based on linguistic judgements given by decision makers who are a group of researchers from the cloud provider company. Figure 3 depicts the hierarchy structure of the cloud service selection. This hierarchy structure consists of three levels: the first, an objective or goal for the problem; the second, criteria (Cr_1 through Cr_5 in Fig. 3); and the third, the alternatives (A_1 through A_{19}).

For each service, the specified data for price/h (dollars), number of virtual cores, and memory (GB) were collected from the respective cloud service providers, and the values for I/O operational consistency, disc storage performance, processing performance, and memory performance were obtained from cloudharmony.com. We performed a consistency check while collecting data to identify data that were logically inconsistent or out of range. Inconsistent data were corrected if possible; otherwise, we excluded the service provider from the analysis. Our data set was limited, having certain QoS attributes for seven cloud service providers. However, collecting these real-world data on cloud service providers was extremely challenging. Our data set is open to use by researchers for the purpose of further research.

We used AHP to compute the weight w_j for the criterion of the QoS parameters of cloud service. The scale that we use ranges from 1 to 9 is described in Table 4, and the weights of each criterion are described in Table 5. The pairwise comparison was made by domain experts. We achieve the *consistency ratio* as 0.0511134. As *consistency ratio* is less than or equal to 0.1, our model is consistent, and weights are valid.

The scale of criteria rating that is used for evaluating ranking of the alternatives linguistic variables is represented in Table 6. Table 7 represents the criteria rating with respect to alternatives and grey decision matrix. The grey normalized decision matrix for cloud services is represented in Table 8 [based on Eq. (4)]. Then, we determine positive ideal solution (A^*) and negative ideal solution (A^-) as shown in Table 9. To obtain A^* and A^-, we compute the maximum upper limit of criteria Q_1 is 1 and the lower limit is 0.19. Afterwards, we calculate separation measure of the positive ideal solution (d_i^*) and negative ideal solution (d_i^-) as shown in Table 9. Subsequently, we determine the relative closeness coefficient (C_i^*) as shown in Table 9. From Table 9, we observe that alternative A_{12} is the best cloud service, followed by alternatives $A_9 > A_8 > A_{14} > A_7 > A_{16} > A_{19} > A_{11} > A_{13} > A_6 > A_2 > A_{17} > A_{15} > A_3 > A_5 > A_{18} > A_1 > A_{10} > A_4$.

Table 7 Criteria rating for cloud services

Q_i	A_i	D_1	D_2	D_3	D_4	$\otimes G_{ij}$	Q_i	D_1	D_2	D_3	D_4	$\otimes G_{ij}$
Q_2	A_1	VP	P	VP	P	[1.41, 2.45]	Q_1	M	MH	MH	M	[3.46, 4.47]
	A_2	F	M	F	MG	[4.23, 5.23]		M	ML	L	L	[5.18, 6.19]
	A_3	P	P	P	P	[2.00, 3.00]		L	VL	VL	VL	[6.74, 7.74]
	A_4	F	MG	F	F	[4.23, 5.23]		H	H	H	VH	[1.68, 2.71]
	A_5	P	MP	P	P	[2.21, 3.22]		VL	VL	L	ML	[6.19, 7.20]
	A_6	F	MG	G	F	[4.68, 5.69]		ML	ML	L	H	[4.16, 5.24]
	A_7	G	G	G	MG	[5.73, 6.74]		L	M	ML	L	[5.18, 6.19]
	A_8	VG	VG	G	VG	[6.74, 7.74]		ML	ML	L	VL	[5.69, 6.70]
	A_9	G	G	G	G	[6.00, 7.00]		L	L	L	L	[6.00, 7.00]
	A_{10}	P	P	VP	MP	[1.86, 2.91]		VH	H	H	H	[1.68, 2.71]
	A_{11}	G	G	MG	G	[5.73, 6.74]		ML	L	ML	ML	[5.23, 6.24]
	A_{12}	VG	G	VG	G	[6.48, 7.48]		VL	VL	VL	L	[6.74, 7.74]
	A_{13}	MG	G	G	MG	[5.48, 6.48]		VL	L	VL	L	[6.48, 7.48]
	A_{14}	G	G	VG	VG	[6.48, 7.48]		ML	ML	ML	L	[5.23, 6.24]
	A_{15}	F	P	MP	MP	[2.91, 3.94]		L	L	L	VL	[6.24, 7.24]
	A_{16}	G	G	MG	G	[5.73, 6.74]		ML	ML	L	H	[4.16, 5.24]
	A_{17}	F	MG	G	F	[4.68, 5.69]		M	MH	MH	M	[3.46, 4.47]
	A_{18}	MG	G	G	MG	[5.48, 6.48]		H	H	H	VH	[1.68, 2.71]
	A_{19}	MG	G	G	VG	[6.48, 7.48]		VL	L	L	L	[6.24, 7.24]
Q_3	A_1	MG	G	G	G	[5.73, 6.74]	Q_4	VP	P	VP	P	[1.41, 2.45]
	A_2	MG	F	G	F	[4.68, 5.69]		F	M	F	MG	[4.23, 5.23]
	A_3	P	P	P	VP	[1.68, 2.71]		P	P	P	P	[2.00, 3.00]
	A_4	MP	MP	P	P	[2.45, 3.46]		F	MG	F	F	[4.23, 5.23]
	A_5	MP	P	P	VP	[1.86, 2.91]		P	MP	P	P	[2.21, 3.22]
	A_6	G	G	G	G	[6.00, 7.00]		F	MG	G	F	[4.68, 5.69]
	A_7	G	VG	MG	VG	[6.19, 7.20]		G	G	G	MG	[5.73, 6.74]
	A_8	G	G	VG	MG	[5.69, 6.96]		VG	VG	G	VG	[6.74, 7.74]
	A_9	G	G	VG	VG	[6.48, 7.48]		G	G	G	G	[6.00, 7.00]
	A_{10}	G	G	G	MG	[5.73, 6.74]		P	P	VP	MP	[1.86, 2.91]
	A_{11}	F	MP	P	F	[3.13, 4.16]		G	G	MG	G	[5.73, 6.74]
	A_{12}	G	MG	MG	VG	[5.69, 6.70]		VG	G	VG	G	[6.48, 7.48]
	A_{13}	P	P	P	MP	[2.21, 3.22]		MG	G	G	MG	[5.48, 6.48]
	A_{14}	VG	VG	VG	VG	[7.00, 8.00]		G	G	VG	VG	[6.48, 7.48]
	A_{15}	P	P	MP	MP	[2.45, 3.46]		F	P	MP	MP	[2.91, 3.94]
	A_{16}	VG	G	MG	MG	[5.69, 6.70]		G	G	MG	G	[5.73, 6.74]
	A_{17}	G	G	G	G	[6.00, 7.00]		F	MG	G	F	[4.68, 5.69]
	A_{18}	F	MP	P	F	[3.13, 4.16]		MG	G	G	MG	[5.48, 6.48]
	A_{19}	MP	P	P	VP	[1.86, 2.91]		MG	G	G	VG	[6.48, 7.48]

7 A comprehensive analysis of extended Grey TOPSIS

We present a comprehensive analysis of the proposed approach, considering the following factors:

- Sensitivity to the weights assigned to output parameters
- Effectiveness under change in the alternatives
- Adequacy to support group decision-making
- Handling of uncertainty.

7.1 Sensitivity analysis

The sensitivity analysis determines the robustness of our proposed approach. We tested the effect of a change in priorities and final weights on the proposed approach (Saltelli et al. 2000). For each QoS parameter, we experimented with varying priorities and their corresponding final weights. We moderately adjusted the weights of the QoS parameters one at a time and observed the impact of the changes in weights

Table 8 Extended grey normalized decision matrix for cloud services

	Q_1		Q_2		Q_3		Q_4		Q_5	
A_1	0.43	0.56	0.19	0.32	0.72	0.85	0.19	0.32	0.72	0.85
A_2	0.21	0.34	0.55	0.68	0.72	0.72	0.55	0.68	0.59	0.72
A_3	0	0.13	0.26	0.39	0.21	0.34	0.26	0.39	0.21	0.34
A_4	0.65	0.79	0.55	0.68	0.31	0.44	0.55	0.68	0.31	0.44
A_5	0.07	0.21	0.29	0.42	0.24	0.37	0.29	0.42	0.24	0.37
A_6	0.33	0.47	0.6	0.74	0.75	0.88	0.61	0.74	0.75	0.88
A_7	0.21	0.34	0.74	0.88	0.78	0.9	0.75	0.88	0.78	0.90
A_8	0.14	0.27	0.87	1	0.72	0.87	0.88	1	0.72	0.87
A_9	0.1	0.23	0.77	0.91	0.81	0.94	0.78	0.91	0.81	0.94
A_{10}	0.65	0.79	0.24	0.38	0.72	0.85	0.25	0.38	0.72	0.85
A_{11}	0.2	0.33	0.74	0.88	0.4	0.52	0.75	0.88	0.4	0.52
A_{12}	0	0.13	0.83	0.97	0.72	0.84	0.84	0.97	0.72	0.84
A_{13}	0.04	0.17	0.7	0.84	0.28	0.41	0.71	0.84	0.28	0.41
A_{14}	0.2	0.33	0.83	0.97	0.88	1	0.84	0.97	0.88	1
A_{15}	0.07	0.2	0.37	0.51	0.31	0.44	0.38	0.51	0.31	0.44
A_{16}	0.33	0.47	0.74	0.88	0.72	0.84	0.75	0.88	0.72	0.84
A_{17}	0.43	0.56	0.6	0.74	0.75	0.88	0.61	0.74	0.75	0.88
A_{18}	0.65	0.79	0.7	0.84	0.4	0.52	0.71	0.84	0.4	0.52
A_{19}	0.07	0.2	0.83	0.97	0.24	0.37	0.84	0.97	0.24	0.37

Table 9 Extended Grey TOPSIS analysis results for cloud services

	d_i^*	d_i^-	A^*	A^-	C_i^*	Rank
A_1	0.563162	0.349619	1	0.19	0.383026	17
A_2	0.340162	0.473053	0	0.79	0.581707	11
A_3	0.562498	0.447627	1	0.21	0.44314	14
A_4	0.5896	0.287524	1	0.19	0.327803	19
A_5	0.544004	0.410383	1	0.21	0.429996	15
A_6	0.33499	0.492483			0.595165	10
A_7	0.227103	0.591541			0.722586	5
A_8	0.178727	0.655258			0.785695	3
A_9	0.166872	0.649084			0.795489	2
A_{10}	0.619909	0.311969			0.334774	18
A_{11}	0.343847	0.517125			0.60063	8
A_{12}	0.148246	0.686024			0.822305	1
A_{13}	0.372908	0.554014			0.597693	9
A_{14}	0.184493	0.659408			0.78138	4
A_{15}	0.48123	0.434997			0.47477	13
A_{16}	0.29645	0.53956			0.645399	6
A_{17}	0.377354	0.467993			0.55361	12
A_{18}	0.534066	0.390268			0.422215	16
A_{19}	0.373112	0.595637			0.614852	7

on the final decisions (Christopher Frey and Patil 2002). In this way, the performance of each QoS parameter and its results were analysed and applied to the extended version of Grey TOPSIS. The sensitivity analysis for processing performance, I/O operational consistency, disc storage performance, and memory performance parameters against 19 cloud services of EGTOPSIS are depicted in Figs. 4, 5, 6, and 7, respectively. In Figs. 4, 5, 6, and 7 the cloud services or alternatives and efficiency scores of the alternatives are presented on the x-axis and y-axis, respectively.

We analysed the efficiency scores of the alternatives by varying the weights of the processing performance, I/O operational consistency one at a time and reported the efficiency scores in descending order for each attribute. We noted the top ten alternatives that gave the best efficiency scores for different weights in all of the cases. From Fig. 4, we perceive that alternatives A_{12}, A_9, A_8, A_{14}, A_7, A_{16}, A_{19}, A_{11}, A_{13}, and A_6 (i.e. descending order) give the efficiency scores for the various weights of processing performance attribute. Likewise, in Fig. 5, the alternatives A_{12}, A_8, A_9, A_{14}, A_7, A_{16}, A_{19}, A_{11}, A_{13}, and A_6 (i.e. descending order) gave the best efficiency scores for different weights of I/O operational consistency attribute. From Fig. 6, we notice that alternatives A_{12}, A_9, A_8, A_{14}, A_7, A_{16}, A_{19}, A_{11}, A_{13}, and A_6 (i.e. descending order) give the best efficiency scores for different weights of disc storage performance attribute. Similarly, in Fig. 7, we notice that alternatives A_{12}, A_8, A_9, A_{14}, A_7, A_{16}, A_{19}, A_{11}, A_{13}, and A_6 (i.e. descending order) give the best efficiency scores for different weights of memory performance attribute.

Based on our experiments, we observed that the priority of a alternative is proportional to the weight of the corresponding attribute and that these changes have no significant effect

Fig. 4 Sensitivity analysis of EGTOPSIS for processing performance

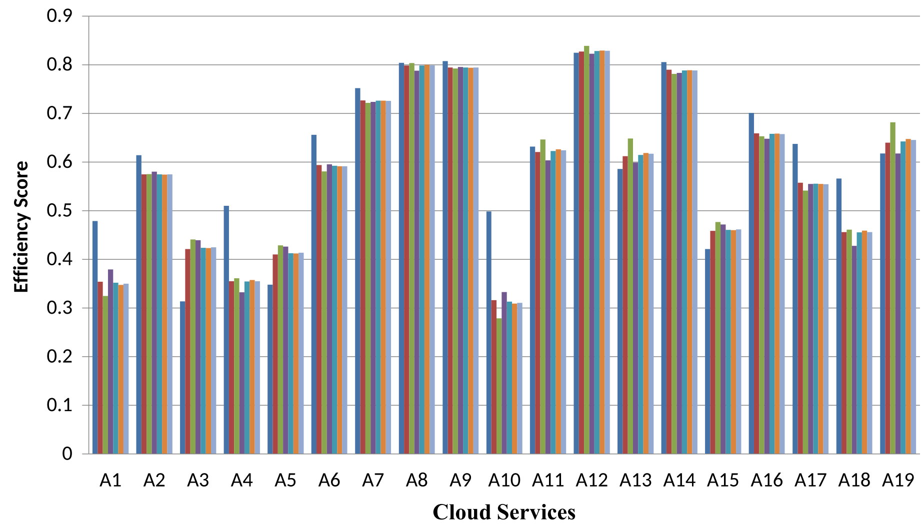


Fig. 5 Sensitivity analysis of EGTOPSIS for I/O operational consistency

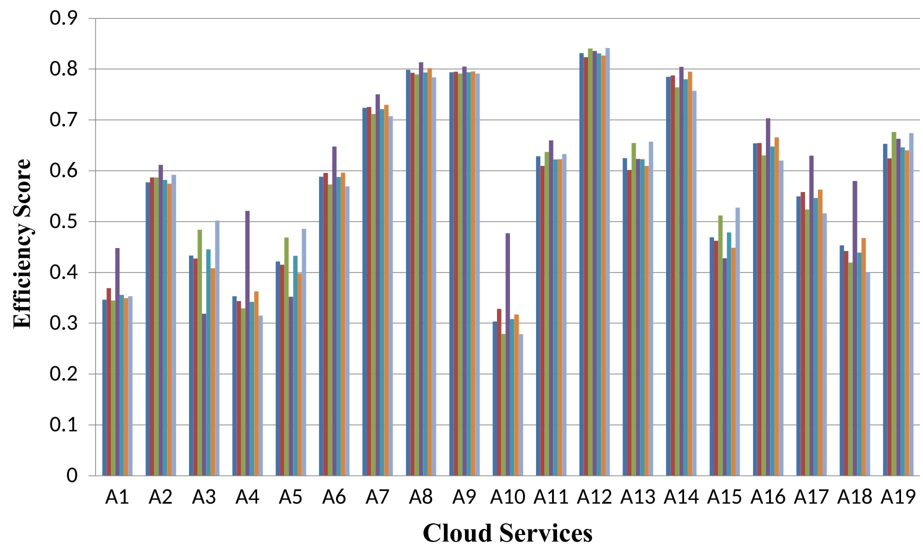
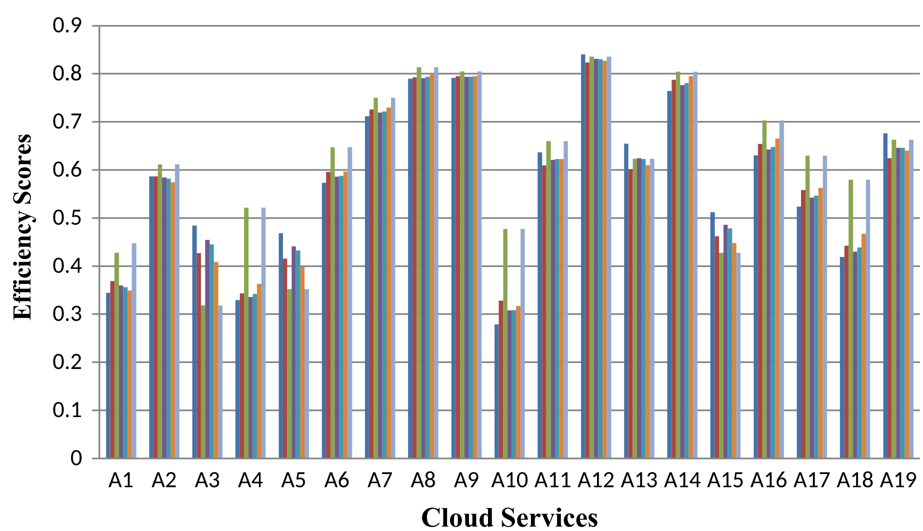


Fig. 6 Sensitivity analysis of EGTOPSIS for disc storage performance



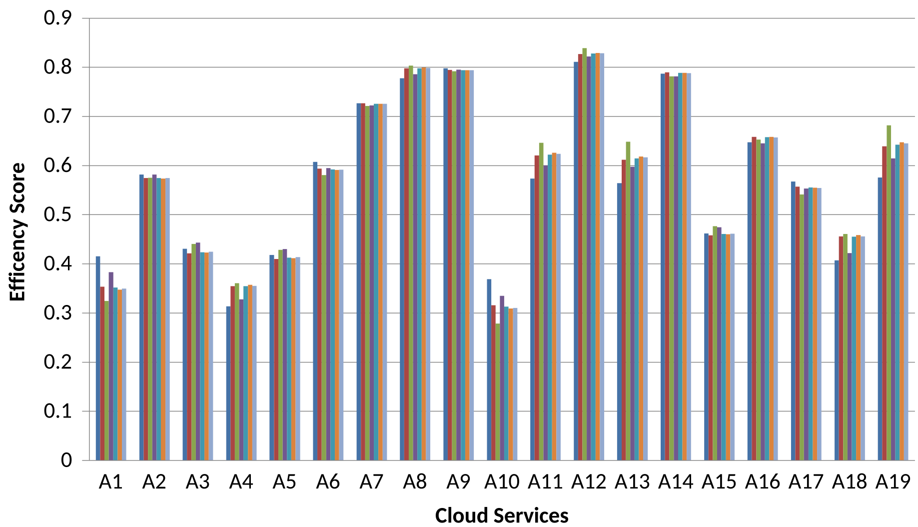


Fig. 7 Sensitivity analysis of EGTOPSIS for memory Performance

on the alternatives ranking and efficiency. In addition, the final decision does not change in most of the cases. Likewise, we determine the sensitivity analysis of other two criteria: disc storage performance and memory performance. After all of these experiments, we found that alternative A_{12} is the best cloud service in all cases and also has a high number of virtual cores (i.e. eight).

7.2 Adequacy under change in alternatives

For evaluating the efficiencies of different cloud services, we may require some inclusion and exclusion criteria on cloud services. Cloud service selection on the basis of efficiency implies a consistent order of priorities for cloud service. In the extended version of Grey TOPSIS application cases, with 19 alternatives and equal weights for all criteria, the ranking is (A_{12}, A_9, A_8, A_{14}, A_7, A_{16}, A_{19}, A_{11}, A_{13}, A_6, A_2, A_{17}, A_{15}, A_3, A_5, A_{18}, A_1, A_{10}, and A_5). To test the extended version of Grey TOPSIS, we added an additional alternative with equal priority weights to the existing alternatives. In most of the test cases, the results do not show any significant changes in the ranking of alternatives. The order of priority remains the same in all cases tested, and the results do not show any changes in the ranking of the alternatives.

7.3 Adequacy to support group decision-making

Generally, the fuzzy TOPSIS and extended Grey TOPSIS methods allow aggregation of the judgements of multiple decision makers. The quantity of data needed by fuzzy TOPSIS is always more than for the extended Grey TOPSIS methods. An increase in the number of decision makers will accordingly cause a large increase in the computational complexity of fuzzy TOPSIS as compared to the extended Grey TOPSIS. Because of the influence of computational complexity, the extended version of Grey TOPSIS is preferable to the improved TOPSIS (Sidhu and Singh 2017) and fuzzy TOPSIS (Kumar et al. 2017).

7.4 Handling of uncertainty

Generally, in fuzzy TOPSIS and Grey TOPSIS methods, we utilize fuzzy set theory to deal with the intrinsic lack of clarity in the data for selecting cloud services. In these methods, the fuzzy number structure is the main resource for quantifying vagueness. Owing to the uncertainty of judgements of quantitative variables, triangular membership function parameters are selected. To evaluate the alternatives, the decision makers used linguistic terms for the different decision criteria. In EGTOPSIS, we employed a pairwise comparison using comparative linguistic variables.

8 Conclusions and future work

As there are several cloud services with different quality-of-service (QoS) parameters, the selection of a suitable cloud service becomes challenging for users. To select appropriately among different cloud services, users look for QoS parameters of cloud services. This paper presented the a hybrid multi-criteria decision- making model for cloud service selection using extended version of Grey TOPSIS. In this paper, AHP is used to ascertain the weights of criteria and integrated with Grey TOPSIS to evaluate the ranks of the alternatives. Grey numbers are included in TOPSIS to deal with the uncertainties embedded in cloud service selection.

In this paper, we determined the weights of QoS parameters by applying AHP method. Using AHP, we prioritized the criteria in the descending order of price (0.34523), processing performance (0.28998), memory performance (0.19294), disc storage performance (0.10381), and I/O operational consistency (0.068047), respectively. A_{12} is emerged as the best alternative by applying our extended Grey TOPSIS, respectively. Further, we conducted sensitivity analysis, adequacy of changes of alternatives, adequacy to support decision-making, modelling of uncertainty, and computational complexity for our proposed method. In our future work, we explore the ways of integrating the fuzzy operators with hybrid computational intelligence methods and data mining approaches.

Compliance with ethical standards

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of interest All authors declare that they have no conflict of interest.

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