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Conflict of Interest

Here both the authors declare that they do not have any conflict of interest.

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A Framework for Prioritizing Cloud Services in Neutrosophic Environment

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A Framework for Prioritizing Cloud Services in Neutrosophic Environment

Abstract: Cloud service selection assists cloud users to find the best cloud services as per their needs and minimizes the loss occurring due to improper selection of services. This paper aims to develop a cloud service selection framework for the neutrosophic environment using single-valued neutrosophic set (SVNS) theory and multi-criteria decision making (MCDM) based technique for order of preference by similarity to ideal solution (TOPSIS). The SVNS helps cloud users and experts to express their opinion in linguistic terms rather than crisp value due to partial knowledge involving some degree of truth, indeterminacy and falsehood. TOPSIS is used to rank cloud services efficiently. A case study has been performed on a real dataset obtained from CloudHarmony to demonstrate its practicality and usefulness. Sensitivity analysis has been carried out with the addition and deletion of cloud services to rank them and found that the framework is consistent and robust to rank reversal problem. The framework is also capable to strongly handle a fuzzy environment without rank reversal phenomenon in comparison with other MCDM based cloud service selection frameworks available in the literature.

Keywords: MCDM, Cloud Service Selection, TOPSIS, Neutrosophic Set Theory, Cloud User, Cloud Service Provider

1. Introduction

The importance of scalable applications has led the business organization to deploy their applications on the cloud. Cloud computing provides the flexibility for dynamic provisioning of resources to the applications as per their requirements. It provides resources like computing power, networking, storage, platform and application support on a subscription basis to the users anytime and anyplace. It mainly provides three types of service models namely infrastructure as a service (IaaS), platform as a service (Pass) and software as a service (SaaS) to offers various services to the users. IaaS provides computing support to cloud customers, PaaS provides a platform to develop the applications whereas SaaS provides readymade applications to the user for their use. Many big organizations like Microsoft, Google, IBM, Amazon, etc. are investing huge capital in offering different cloud services due to numerous applications and flexibility of using cloud services. Besides many prominent organizations, small organizations are also investing capital in the cloud due to its future scope and utility. The exponential increase in cloud service providers (CSP) (Buyya et al., 2009) has posed a challenge for cloud users to find the best CSP as per their necessary and desirable requirements. It has become a challenge for cloud users to find and differentiate CSPs based on QoS (Ardagna et al., 2014) provided by them as some CSPs provide some QoS of high quality whereas lacks in other QoS, that is provided by other CSPs in good quality. It is always the case that more than one CSP fulfills the cloud user requirements and it becomes hard for cloud users to choose a CSP for cloud service. So, there is a need for designing a framework that can assist cloud users to find the optimal CSP as per their needs.

The trivial approach used by cloud users to find the best CSP is based on reports published by cloud benchmark service providers (CloudHarmony, 2019; CloudSpectator, 2019) which evaluates the performance of various CSPs and publishes it through reports. However, the performance measured by the third party in an environment differs from the execution environment of cloud users. So, the selection of CSP involves the evaluation of various CSPs by experts or cloud users based on their experience. The selection of right CSP for a cloud user requires a set of QoS parameters to measure the cloud service performance and a method to rank the CSPs. The cloud service measurement initiative consortium (CSMIC) (SMI framework, 2019) has identified a set of QoS metrics for measuring the various aspect of a cloud service and called it as service measurement index (SMI). The ranking or selection of best CSP is an MCDM problem that aims to select the best CSP based on various QoS parameters. The various authors have used MCDM methods like analytic hierarchy process (AHP) (Saaty, 1990), TOPSIS (Hwang and Yoon 1981), fuzzy TOPSIS (Kumar et al., 2017), fuzzy AHP, multi-attribute utility theory (MAUT) (Dyer, 2005), analytic network process (ANP) (Vargas, 1990), simple additive weighting (SAW) (Afshari et al., 2010), rank voting method, elimination and choice expressing reality (ELECTRE) (Fülöp, 2005), VIKOR (Opricovic et al., 2004), etc. to rank the services in various decision-making problems. The methods like TOPSIS, SAW, AHP, ANP, ELECTRE and VIKOR are used to compute the rank of cloud services based on quantitative QoS metrics. Fuzzy AHP and fuzzy TOPSIS are incorporated with fuzzy set theory to rank the cloud services in a fuzzy environment and are useful for cloud users as the cloud experts prefer to express their opinion in the linguistic term.

The fuzzy set theory maps the cloud expert opinion in linguistic terms to a membership value. However, it is not always the case that expert opinion is focused on membership value. Sometimes an expert is itself not sure while expressing their opinion and it is divided into three significant components- truth, indeterminacy and falsity. So, in these scenarios the cloud service selection frameworks developed for ordinary fuzzy environment fails to provide a suitable CSP to cloud users as per their need. So, we have proposed a cloud service selection framework by integrating the SVNS with the TOPSIS method to select the best CSP. SVNS (Biswas et al., 2016; Abdel-Basset et al., 2019) has been used for mapping the expert opinion to membership, indeterminacy and non-membership values whereas the rank of the cloud services is computed using modified TOPSIS. TOPSIS has been used to rank the cloud services in comparison to other MCDM methods like complex proportional assessment (COPRAS) and multi-attributive border approximation area comparison (MABAC) due to its wide application in solving decision-making problems in literature. AHP and ANP methods become complex (Mousavi-Nasab et al. 2017) as the number of alternatives increases whereas TOPSIS efficiently ranks the alternatives and do not depend on their numbers. Jahan et al. (2010) suggested that TOPSIS is more efficient than VIKOR.

We have considered SVNS in comparison to other fuzzy extensions to handle vagueness due to its advantages over others. The fuzzy set theory introduced by Zadeh (1965) uses a membership function to map a linguistic term to a membership value. Sometimes, different experts have different membership value for a term, e.g. one expert can have a membership value of 0.1 for term low whereas another expert can have membership value as 0.15. So, to deal with the above situation, an extension of the fuzzy set theory called interval value fuzzy set (IVFS) (Gorzałczany, 1987) was introduced which provides flexibility to experts to have a membership value from a range [0,1]. Another extension of the fuzzy set known as hesitant fuzzy set (HFS) (Torra, 2010) allows the experts to map a term to a membership value from a set of membership values. Sometimes, the expert is not confident and has vagueness in their opinion. So, to deal with above problem many extensions of fuzzy set theory were introduced. The intuitionistic fuzzy set (IFS) (Atanassov, 1986) has membership and non-membership value for each element of a set, which provides flexibility to experts when they are not confident about their opinion. IFS has a constraint that the sum of membership and non-membership value can range between 0 and 1, i.e. non-membership value is equal to one minus membership value. Interval value intuitionistic fuzzy set (IVIFS) is an extension of IFS which allows both membership and non-membership value can have a value from a range [0,1]. The intuitionistic fuzzy set of type 2 (IFS2) also maps each element of a set with a membership and non-membership value. It says that membership and non-membership values can range between [0,1] but the sum of their square should be always less or equal to 1. It helps experts to rate a term with membership and non-membership value independently.

Picture fuzzy set theory (PFS) (Cuong et al., 2013) allows each element to have positive, negative and neutral membership value. It is helpful in a situation when experts are unaware of the decision problem. PFS states that the sum of positive, negative and neutral membership values should be always less or equal to one means experts can express their opinion in such a way that the sum of positive, negative and neutral value should be always equal or less to one. Spherical fuzzy set (SFS) (Kutlu et al., 2019) provides flexibility to experts to have independent membership, non-membership and hesitancy value for an element with a constraint that sum of their square should be always less or equal to one. Neutrosophic set (NS) theory helps experts to express their opinion in three significant components- truth, indeterminacy and falsity given that the sum of all three membership values should be less or equal to three. Figure 1 shows the geometric representation of various extensions of the fuzzy set theory. It can be inferred from Figure 1 that NS is a generalization of all the fuzzy set extensions.

So, we have used SVNS for cloud service selection in our study as it provides flexibility to decision-makers to express their opinion in terms of truth, indeterminacy and falsity membership value and all the membership values can be independent of each other. The proposed framework takes the expert opinion about different CSPs based on different QoS metrics and the weight of cloud users for each QoS to rank the cloud services and returns their rank in ascending order. The proposed framework is robust to rank reversal problem and it has been verified through an experiment.

The main contributions of the paper are summarized as follows:

1. Integrated neutrosophic set theory with modified TOPSIS for ranking cloud services for the first time.
2. A sensitivity analysis has been performed to demonstrate the robustness of the proposed framework against rank reversal problem.
3. A comparison of the proposed framework with the cloud service selection frameworks based on fuzzy TOPSIS, improved TOPSIS, AHP, neutrosophic TOPSIS and neutrosophic VIKOR has been performed.
4. Performance analysis has been carried out by measuring the execution time of the framework along with neutrosophic TOPSIS and VIKOR with different number of CSPs.

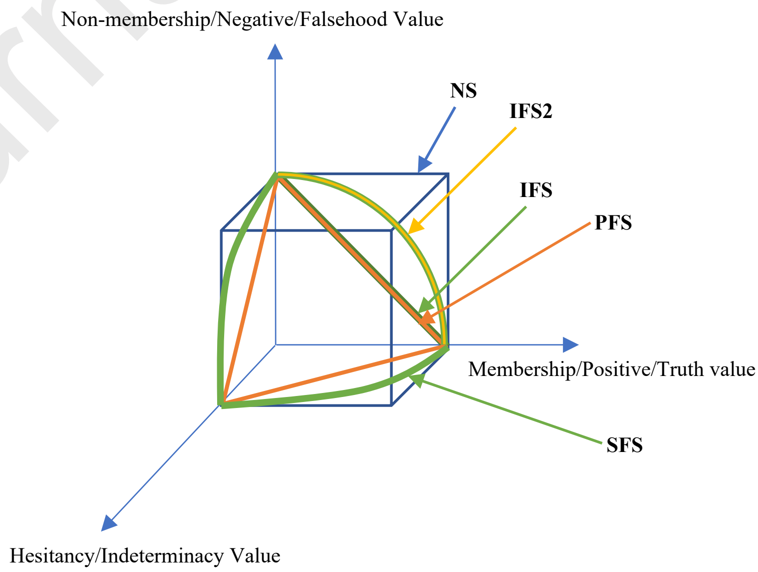

Fig. 1 Geometric representation of various fuzzy set extensions

The remaining part of the paper is organized as follows. Section 2 is devoted to studies that have integrated MCDM methods with neutrosophic set theory as well as MCDM based cloud service selection frameworks available in the literature. Section 3 explains the preliminaries, that have been used in the proposed framework for cloud service selection in the neutrosophic environment. Section 4 focuses on the proposed cloud service selection framework and its main components followed by cloud service ranking using the modified neutrosophic TOPSIS (N-TOPSIS) method in section 5. Section 6 demonstrates a case study to validate the correctness and usefulness of the framework. Finally, we have concluded our work and provided future directions in section 7.

2. Literature Review

The growing market of cloud and the exponential increase in the number of CSPs have attracted researchers to study their performance for different applications like e-commerce, web application, resource management, etc. The focus of researchers was to assess the performance of CSPs and designing frameworks to find appropriate cloud services. The MCDM methods have been extensively used in literature to solve the selection problem in various fields like supplier, automobile, weapon, web service, etc. The researchers have also utilized MCDM methods for cloud service selection similar to web service selection and have been extensively used by different authors in the past few years. Since our proposed framework uses neutrosophic set with TOPSIS to find the best cloud services. We have first reviewed various works based on the integration of neutrosophic set theory with MCDM methods to solve various decision problems and then reviewed MCDM based cloud service selection frameworks. Subsequently, we identified the gaps in MCDM based cloud service selection frameworks and presented a new framework in a later section.

Neutrosophic set theory has gained its importance in many decision problems as it provides flexibility to decision-makers to rate the alternatives in linguistic terms. It helps decision-makers to resolve the ambiguity in their opinion and has been integrated with various MCDM methods. Liu et al. (2018) used neutrosophic set theory with decision making trial and evaluation laboratory method (DEMATEL) to solve the transport service provider selection problem. Neutrosophic set was used to map the linguistic rating of experts to neutrosophic values and DEMATEL was used to rank the transport service providers. Abdel-Basset et al. (2018) integrated neutrosophic set theory with DEMATEL to analyze the supplier selection criteria for the supply chain management. Neutrosophic set was used to adjust the judgment of experts and DEMATEL was used to find the most influencing criteria affecting the supply chain management. Karaşan et al. (2019) integrated neutrosophic set with combinative distance-based assessment (CODAS) to find the wind energy plant location. They used interval value neutrosophic set to deal with the uncertainty while CODAS was used to find the best location for a wind energy plant. Karaşan et al. (2018) also integrated evaluation based on distance from average solution (EDAS) with neutrosophic set to prioritize the sustainable development goal of the United Nations. Karaşan et al. (2019) integrated combined compromise solution (COCOSO) with neutrosophic set and illustrated its application for the selection of disposal waste sites. Abdel-Basset et al. (2018) extended AHP with the neutrosophic set for strengths, weaknesses, opportunities and threats (SWOT) analysis for strategic planning. Abdel-Basset et al. (2018) have also extended ANP and TOPSIS with the neutrosophic set theory for supplier selection problem. So, from the above discussions, we can infer that the neutrosophic set has been integrated with various MCDM methods to solve various selection problems.

Cloud service selection is one of the important challenges in the field of cloud computing for cloud users. Various authors have proposed methods for cloud service selection. Godse et al. (2009) developed a method for SaaS service selection using AHP method. They used various QoS metrics like usability, cost, functionality, architecture and vendor reputation to evaluate the SaaS service and AHP was used to rank them. A case study on Salesforce automation service was performed to show the usefulness of the approach. Dastjerdi et al. (2011) have presented a taxonomy for QoS management in the cloud and explored the selection problem in different contexts like web service, grid, etc. and how it can be mapped in a cloud environment. They broadly classified the MCDM methods into two categories: outranking approach and MAUT. They demonstrated MAUT category approach using AHP for cloud service selection. Rehman et al. (2012) show the usefulness of MCDM techniques for IaaS service selection. They demonstrate the application of PROMETHEE, AHP, ELECTRE and TOPSIS methods for IaaS selection. Whaiduzzaman et al. (2014) presented a taxonomy of cloud service selection based on MCDM methods. They discussed different MCDM methods with their comparative analysis and their applications in various fields.

Garg et al. (2013) developed a framework called SMICloud to rank cloud services using AHP method. They formulated equations to quantify the various functional and non-functional QoS parameters of the SMI framework. The priority of each QoS metric used in the selection of cloud services are computed using AHP. Finally, the priority vector of all QoS metrics were aggregated to rank the cloud services. Baranwal et al. (2016) developed an improved rank voting method based framework to rank cloud services. They also identified a few more QoS parameters to extend the existing SMI framework that helps cloud user to evaluate the cloud services.

They categorized the QoS metrics into two broad categories namely user-specific and application-specific. User-specific QoS is important from the user-specific point of view and consists of QoS related to cloud user experience while application-specific is related to application performance. The improved rank voting method was used to select the best cloud service. It considers cloud services as candidates and QoS provided by them as a voter. Each CSP is ranked for each QoS based on services provided by them. Finally, the ranks of each CSP corresponding to each QoS are aggregated to compute the best cloud service.

Sidhu et al. (2017) designed a new trust evaluation framework using AHP and TOPSIS to find a trusted cloud service. The importance of each QoS parameter is calculated from subjective assessments of each QoS by cloud users using AHP. The TOPSIS was used to find the best cloud service based on their service quality and weight calculated using AHP. Tripathi et al. (2017) presented a method to evaluate cloud services in the presence of interdependent QoS metrics. Their framework uses ANP to model the interaction of QoS parameters and ranking cloud services. ANP represents the cloud services and QoS parameter as a node of the directed graph and edges for interdependency. The priority of interdependent metrics is computed using the pairwise comparison matrix and all priority vectors are aggregated to rank cloud services. ANP becomes complex with the increase in number of cloud services and QoS parameters.

Kumar et al. (2017) presented a cloud service selection framework for the fuzzy environment which provides flexibility and enables cloud experts and users to express their opinion in linguistic terms. They used AHP and fuzzy TOPSIS for cloud service selection. The QoS parameters weight was computed using AHP while TOPSIS was integrated with a triangular fuzzy number to handle fuzziness and rank cloud services. Kumar et al. (2018) also proposed another framework by integrating AHP and TOPSIS to rank cloud services in a crisp environment. The weight of each QoS metrics from the subjective assessment of cloud users is computed using the AHP method. Finally, cloud services were ranked using TOPSIS based on their QoS assessment reports of cloud benchmark service providers. Lee et al. (2016) developed a framework to find the best IaaS cloud service in a fuzzy environment. They used balanced scorecard to identify the QoS metrics important from aspects like financial, business process etc. and fuzzy Delphy method to find the most important QoS parameters from each aspect. Finally, AHP with triangular fuzzy numbers was used to aggregate and compute the priority vector of each QoS parameters to rank the cloud services.

Radulescu et al. (2017) presented a framework to rank cloud services based on entropy and extended TOPSIS method. The weights of QoS parameters were computed using the entropy method. They modified the traditional TOPSIS by replacing Equilidean distance with Minkowski distance and used it to select the best cloud service. Basu et al. (2018) developed a rank reversal robust framework to rank cloud services in the fuzzy environment using fuzzy TOPSIS. But, it fails to handle interdependent QoS metrics. Basset et al. (2018) integrated neutrosophic set theory with AHP to rank cloud services. Single valued neutrosophic triangular numbers were used to handle the uncertainty and AHP was used to rank cloud services. The neutrosophic AHP proposed by them was robust to handle inconsistent pairwise matric in comparison to AHP and fuzzy AHP, but its complexity increases with the increase in the number of cloud service providers. Jatoth et al. (2019) proposed a service selection framework using AHP and Grey TOPSIS. They used AHP to compute the importance of QoS parameters and integrated Grey set theory with TOPSIS to rank the cloud services.

It can be noted from the above discussions that cloud service selection is a decision-making problem and most of the authors have used MCDM methods to choose the best CSP. The cloud service selection frameworks reviewed in the literature works either for a crisp or fuzzy environment but not for the neutrosophic environment effectively. Neutrosophic set theory has gained its importance in recent years to tackle the problem of uncertainty more effectively. So, we have integrated neutrosophic set theory with the modified TOPSIS method to rank the cloud services for the first time. The new model is efficient and ranks cloud services in the neutrosophic environment robustly. We believe that this study is the first to use the modified N-TOPSIS for cloud service ranking.

3. Preliminaries

In this section, the various preliminary used for developing the cloud service selection in the neutrosophic environment have been discussed. Initially, we have discussed the neutrosophic set theory and its various operators. Finally, the modified N-TOPSIS method has been discussed for ranking cloud services.

I. Neutrosophic Set Theory

Florentinc Smarandache coined the notion of neutrosophic set theory in 1998. It is an extension of intuitionistic fuzzy set theory where each element comprises a degree of membership as well as non-membership. In neutrosophic set theory, each element has a degree of indeterminacy besides the membership and non-membership degree value as sometimes the decision-makers are not familiar with the aspects involved in the decision-making process. We will discuss neutrosophic set, single value neutrosophic set and operations involve in it to develop the proposed framework of cloud service selection.

Definition 1 (Smarandache, 1998) A neutrosophic set A in a universe of discourse X is a collection of all elements x such that x∊X and each x is defined by truth membership function $T_A(x)$, indeterminacy membership function $I_A(x)$ and falsehood membership function $F_A(x)$. A neutrosophic set A is denoted by-

$$A = \{\langle x, T_A(x), I(x), F_A(x)\rangle \mid x \epsilon X\} \tag{1}$$

where

$$T_A(x){:}X \to]^-0,1^+[$$

$$I_A(x){:}X \to]^-0,1^+[$$

$$F_A(x){:}X \to]^-0,1^+[$$

$]^-0,1^+[$ represents real standard values between and 0 and 1, non-standard values $^-0$ and 1^+ where $^-0 = 0 - \varepsilon$ and $1^+ = 1+ \varepsilon$. ε is an infinitesimal number. The sum of all three membership values varies between $^-0$ to 3^+.

Definition 2 (Wang et al., 2010) A single value neutrosophic set A in a universe of discourse X is a collection of all elements x such that x∊X and x is defined by truth membership function $T_A(x)$, indeterminacy membership function $I_A(x)$ and falsehood membership function $F_A(x)$. A single value neutrosophic set A is denoted by-

$$A = \{\langle x, T_A(x), I(x), F_A(x)\rangle \mid x \epsilon X\} \tag{2}$$

where

$$T_A(x){:}X \to [0,1]$$

$$I_A(x){:}X \to [0,1]$$

$$F_A(x){:}X \to [0,1]$$

The sum of these three membership values varies from 0 to 3. Usually, a single value neutrosophic set is represented by $\langle T_A(x), I_A(x), F_A(x)\rangle$ for all x in X.

Definition 3 (Ye, 2015) Let A = $\langle T_A(x), I_A(x), F_A(x)\rangle$ and B = $\langle T_B(x), I_B(x), F_B(x)\rangle$ be two single value neutrosophic set in the universe of discourse X, then the following operations are defined as-

$$A \oplus B = \langle T_A(x) + T_B(x) - T_A(x)T_B(x), I_A(x)\, I_B(x), F_A(x)F_B(x)\rangle \tag{3}$$

$$A \otimes B = \langle T_A(x)T_B(x), I_A(x) + I_B(x) - I_A(x)I_B(x), F_A(x) + F_B(x) - F_A(x)F_B(x)\rangle \tag{4}$$

$$\lambda A = \left\langle 1 - (1 - T_A(x))^{\lambda}, (I_A(x))^{\lambda}, (F_A(x))^{\lambda}\right\rangle \, for\ \lambda > 0 \tag{5}$$

$$A^{\lambda} = \left\langle (T_A(x))^{\lambda}, 1 - (1 - I_A(x))^{\lambda}, 1 - (1 - F_A(x))^{\lambda}\right\rangle \, for\ \lambda > 0 \tag{6}$$

Example 1 Let A = ⟨0.8, 0.1, 0.2⟩ and B = ⟨0.6, 0.3, 0.4⟩ are two neutrosophic set, then the various operations discussed above can be performed as-

$$A \oplus B = \langle 0.8 + 0.6 - 0.8 * 0.6, 0.1 * 0.3, 0.2 * 0.4\rangle = \langle 0.92, 0.03, 0.08\rangle$$
$$A \otimes B = \langle 0.8 * 0.6, 0.1 + 0.3 - 0.1 * 0.3, 0.2 + 0.4 - 0.2 * 0.4\rangle = \langle 0.48, 0.37, 0.52\rangle$$

If $\lambda = 0.5$ then

$$\lambda A = \left\langle 1 - (1 - 0.8)^{0.5}, (0.1)^{0.5}, (0.2)^{0.5}\right\rangle = \langle 0.86, 0.32, 0.45\rangle$$
$$A^{\lambda} = \left\langle (0.8)^{0.5}, 1 - (1 - 0.1)^{0.5}, 1 - (1 - 0.2)^{0.5}\right\rangle = \langle 0.89, 0.05, 0.11\rangle$$

Definition 4 Let A = $\langle\langle T_A(x_1), I_A(x_1), F_A(x_1)\rangle, \langle T_A(x_2), I_A(x_2), F_A(x_2)\rangle, \ldots \langle T_A(x_n), I_A(x_n), F_A(x_n)\rangle\rangle$ and B = $\langle\langle T_B(x_1), I_B(x_1), F_B(x_1)\rangle, \langle T_B(x_2), I_B(x_2), F_B(x_2)\rangle, \ldots\ldots \langle T_B(x_n), I_B(x_n), F_B(x_n)\rangle\rangle$ be two single value neutrosophic vector of length of n for $X = \{x_1, x_2 \ldots\ldots, x_n\}$, then the Hamming distance (Ye, J. 2014) between A and B is defined as-

$$D(A,B) = \frac{1}{3}\sum_{i=1}^{n}\left(|T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)|\right) \tag{7}$$

Example 2 Let $A = \langle 0.8, 0.0, 0.4\rangle$, $B = \langle 0.6, 0.0, 0.2\rangle$ and $C = \langle 0.6, 0.0, 0.6\rangle$ and are three single value neutrosophic set, then

$$D(A,B) = \frac{1}{3}(|0.8 - 0.6| + |0.0 - 0.0| + |0.4 - 0.2|) = 0.13$$

$$D(A,C) = \frac{1}{3}(|0.8 - 0.6| + |0.0 - 0.0| + |0.4 - 0.6|) = 0.13$$

We can infer from the truth, indeterminacy and falsity degree of *A, B* and *C* that distance between *A* and *B* is less than *A* and *C*. But using Eq. 7 we get $D(A,B) = D(A,C)$. So, we can say that Eq. 7 is not able to differentiate between *A, B* and *C* as it considers only absolute difference. (Huang, H.L. 2016) investigated the above problem and proposed a new distance measure given in Eq. 8 to eliminate the above problem.

$$D(A,B) = \left[\sum_{i=1}^{n}\left(\sum_{j=1}^{4}\beta_j\phi_j(A_i,B_i)\right)^{\lambda}\right]^{1/\lambda} \tag{8}$$

where $\lambda > 0$, $\beta_i \in [0,1]$, $\sum_{j=1}^{4}\beta_j = 1$ *and*

$$\phi_1(A_i,B_i) = \frac{|T_A(x_i) - T_B(x_i)|}{3} + \frac{|I_A(x_i) - I_B(x_i)|}{3} + \frac{|F_A(x_i) - F_B(x_i)|}{3} \tag{9}$$

$$\phi_2(A_i,B_i) = \max\left(\frac{2 + T_A(x_i) - I_A(x_i) - F_A(x_i)}{3}, \frac{2 + T_B(x_i) - I_B(x_i) - F_B(x_i)}{3}\right) - \min\left(\frac{2 + T_A(x_i) - I_A(x_i) - F_A(x_i)}{3}, \frac{2 + T_B(x_i) - I_B(x_i) - F_B(x_i)}{3}\right) \tag{10}$$

$$\phi_3(A_i,B_i) = \frac{|T_A(x_i) - T_B(x_i) + I_B(x_i) - I_A(x_i)|}{2} \tag{11}$$

$$\phi_4(A_i,B_i) = \frac{|T_A(x_i) - T_B(x_i) + F_B(x_i) - F_A(x_i)|}{2} \tag{12}$$

The distance computed between neutrosophic set *A, B* and *C* of Example 1 using Eq. 8 considering $\lambda = 1$ *and* $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0.25$ is shown below.

$$D(A,B) = 0.0583$$

$$D(A,C) = 0.1417$$

We can observe that $D(A,B) < D(A,C)$, which indicates that Eq. 8 measures the distance correctly.

II. Modified Neutrosophic TOPSIS

TOPSIS is an MCDM method that has been extensively used to solve many complex decision-making problems in various fields like automobile industries (Jain et al., 2018; Kim et al., 2011), the manufacturing system (Rudnik et al., 2017; Yurdakul et al., 2005), route selection for transportation of hazardous materials (Noureddine et al., 2019), etc. It is based on the hypothesis that the alternative which is having the largest geometric distance from a negative ideal solution and closer to the positive ideal solution is the best. The original TOPSIS considers the crisp or accurate judgment of experts for an alternative for a particular criterion, which is not always possible as experts are more comfortable in linguistic judgment than giving a score or number to an alternative. To solve the above problems of experts, Chen (Chen et al., 2006) combined traditional TOPSIS with fuzzy set theory and developed its extension called fuzzy TOPSIS. Fuzzy TOPSIS has been widely used to solve decision problems in a fuzzy environment (Rani et al., 2019; Mishra, 2016). In fuzzy TOPSIS, the experts express their opinion in terms of linguistic terms, which are further mapped to a fuzzy value using a fuzzy membership function. The mapped fuzzy value consists of only membership value. TOPSIS has been also integrated with IFS (Kumari et al., 2019; Mishra et al., 2017) and many other extensions of the fuzzy set to solve various decision problems.

But sometimes while giving an opinion, the expert is not familiar with some aspects of alternatives and lacks knowledge or is more confident about the falsity of their opinion than its truthiness. So, to overcome the above problem, Smarandache (1998) extended the fuzzy set theory to neutrosophic set theory where each linguistic term is mapped to neutrosophic set with three components- membership or truthiness value, indeterminacy or neutral value and non-membership or falsehood value. Smarandache developed N-TOPSIS by extending traditional TOPSIS with neutrosophic set theory to solve MCDM problems in the neutrosophic environment. This study has proposed a different method of computing positive and negative ideal solution in N-TOPSIS. It has also used a distance measure defined in Eq. 8 and proposed a modified N-TOPSIS method for cloud service selection.

The various steps used in the modified N-TOPSIS method to solve a complex MCDM problem are discussed below-

Step 1: Construct Decision Matrix with Single Value Neutrosophic set

Let there are *m* alternatives $(A_1, A_2, A_3, \ldots\ldots A_n)$ and *n* criteria $(C_1, C_2, C_3, \ldots\ldots C_m)$ and expert provides their linguistic opinion for each alternative corresponding to each criterion. The linguistic term is mapped to the neutrosophic set value using a suitable mapping function and the decision matrix is computed. The decision matrix with the neutrosophic set is represented as-

$$D = \begin{bmatrix} \langle T(x_{1,1}), I(x_{1,1}), F(x_{1,1})\rangle & \langle T(x_{1,2}), I(x_{1,2}), F(x_{1,2})\rangle & \cdots & \langle T(x_{1,n}), I(x_{1,n}), F(x_{1,n})\rangle \\ \langle T(x_{2,1}), I(x_{2,1}), F(x_{2,1})\rangle & \langle T(x_{2,2}), I(x_{2,2}), F(x_{2,2})\rangle & \cdots & \langle T(x_{2,n}), I(x_{2,n}), F(x_{2,n})\rangle \\ \vdots & \cdots & \ddots & \vdots \\ \langle T(x_{m,1}), I(x_{m,1}), F(x_{m,1})\rangle & \langle T(x_{m,2}), I(x_{m,2}), F(x_{m,2})\rangle & \cdots & \langle T(x_{m,n}), I(x_{m,n}), F(x_{m,n})\rangle \end{bmatrix} \quad (13)$$

Step 2: Identify the Weight of each Criterion

The expert provides the importance of each criterion in the linguistic term. The linguistic importance given by the expert for each criterion is also converted into the neutrosophic set with the help of a suitable mapping function. The weight matrix for criteria can be represented as:

$$W = [\langle T(w_1), I(w_1), F(w_1)\rangle \quad \langle T(w_2), I(w_2), F(w_2)\rangle \quad \ldots. \quad \langle T(w_n), I(w_n), F(w_n)\rangle] \quad (14)$$

Step 3: Compute Weighted Decision Matrix

The weighted decision matrix in the neutrosophic set is computed by multiplication of decision matrix *D* and weighted vector *W*. It is computed using Eq. 15 as-

$$D^W = (u^w_{i,j})_{mxn} = D \otimes W \quad (15)$$

where

$$u^w_{i,j} = \langle T^w_{i,j}, I^w_{i,j}, F^w_{i,j}\rangle = \langle T(x_{i,j})T(w_j), I(x_{i,j}) + I(w_j) - I(x_{i,j}) * I(w_j), F(x_{i,j}) + F(w_j) - F(x_{i,j}) * F(w_j)\rangle$$

So weighted decision matrix can be represented as-

$$D^W = \begin{bmatrix} \langle T^w_{1,1}, I^w_{1,1}, F^w_{1,1}\rangle & \langle T^w_{1,2}, I^w_{1,2}, F^w_{1,2}\rangle & \cdots & \langle T^w_{1,n}, I^w_{1,n}, F^w_{1,n}\rangle \\ \langle T^w_{2,1}, I^w_{2,1}, F^w_{2,1}\rangle & \langle T^w_{2,2}, I^w_{2,2}, F^w_{2,2}\rangle & \cdots & \langle T^w_{2,n}, I^w_{2,n}, F^w_{2,n}\rangle \\ \vdots & \cdots & \ddots & \vdots \\ \langle T^w_{m,1}, I^w_{m,1}, F^w_{m,1}\rangle & \langle T^w_{m,2}, I^w_{m,2}, F^w_{m,2}\rangle & \cdots & \langle T^w_{m,n}, I^w_{m,n}, F^w_{m,n}\rangle \end{bmatrix} \quad (16)$$

Step 4: Compute the Single Valued Neutrosophic Positive and Negative Ideal Solution

There are two types of criteria namely benefit and cost criteria for selecting the best alternative. Benefit criteria are those criteria whose value expert wants to maximize or whose value should be maximum and cost criteria is one whose value should be minimum. For example, suppose a user wants to buy a computer based on two criteria or parameters- computing power and price, then computing power is benefit criteria and the price is cost criteria as a user will always prefer a computer with maximum computing power with minimum price. The single value neutrosophic positive (SVNPIS) and negative ideal solution (SVNNIS) are computed considering cost and benefit criteria. SVNPIS and SVNNIS represent the ideal and worst alternatives. Let J_1 and J_2 represent the set of benefit and cost criteria considered in the decision-making process, then SVNPIS and SVNNIS are computed using Eq. 17 and Eq. 18 respectively.

$$SVNPIS = A^+ = [\langle T^+_1, I^+_1, F^+_1\rangle \quad \langle T^+_2, I^+_2, F^+_2\rangle \quad \cdots \quad \langle T^+_n, I^+_n, F^+_n\rangle] \quad (17)$$

$$SVNNIS = A^- = [\langle T_1^-, I_1^-, F_1^- \rangle \quad \langle T_2^-, I_2^-, F_2^- \rangle \quad \cdots \quad \langle T_n^-, I_n^-, F_n^- \rangle] \tag{18}$$

where

$$\langle T_j^+, I_j^+, F_j^+ \rangle = \begin{cases} \langle 1.0, 0.0, 0.0 \rangle & for\ j \in J_1 \\ \langle 0.0, 1.0, 1.0 \rangle & for\ j \in J_2 \end{cases}$$

$$\langle T_j^-, I_j^-, F_j^- \rangle = \begin{cases} \langle 0.0, 1.0, 1.0 \rangle & for\ j \in J_1 \\ \langle 1.0, 0.0, 0.0 \rangle & for\ j \in J_2 \end{cases}$$

Step 5: Calculate the distance of each alternative from SVNPIS and SVNNIS

Compute the distance of each alternative from *SVNPIS* (A^+) and *SVNNIS* (A^-). The distance measure that has been used to compute the distance between alternative A_i from A^+ and A^- are shown in Eq. 19 and Eq. 20.

$$D_i^+ = D(A_i, A^+) = \left[\sum_{j=1}^{n} \left(\sum_{k=1}^{4} \beta_k \phi_k (A_{i,j}, A_j^+) \right)^{\lambda} \right]^{1/\lambda} \tag{19}$$

$$D_i^- = (A_i, A^-) = \left[\sum_{j=1}^{n} \left(\sum_{k=1}^{4} \beta_k \phi_k (A_{i,j}, A_j^-) \right)^{\lambda} \right]^{1/\lambda} \tag{20}$$

where D_i^+ and D_i^- represents the distance of i[th] alternative from SVNPIS and SVNNIS respectively. $\lambda > 0$, $\beta_i \in [0,1]$, $\sum_{j=1}^{4} \beta_j = 1$ and $\phi_1, \phi_2\ \phi_3\ and\ \phi_4$ are defined in Eq. 9-12.

Step 6: Calculate the closeness index of each alternative

The closeness index of each alternative is computed using Eq. 21. The closeness index shows how close the alternative is from SVNPIS and SVNNIS.

$$CI_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{21}$$

where CI_i represents the closeness index of alternative i. The closeness index of each alternative is computed for ranking the alternatives.

Step 7: Rank the alternatives

The alternatives are ranked as per descending order of closeness index i.e. the alternative with the highest value of closeness index is ranked best whereas alternative with minimum closeness index value is ranked worst.

4. Proposed Cloud Service Selection Framework

The proposed framework for ranking cloud services in the neutrosophic environment is shown in Figure. 2. The primary entity of the framework is cloud service repository, cloud benchmark service providers, cloud broker, cloud user and cloud service providers. The cloud user interacts with the cloud broker to find the best cloud service. The cloud user provides a set of functional and non-functional QoS parameters and their importance in the form of the linguistic term to cloud broker and cloud broker returns the list of cloud service providers from best to worst as per the requirement of cloud user. The proposed framework uses modified N-TOPSIS to rank cloud services and robust against rank reversal problem as traditional TOPSIS based cloud service selection frameworks (Kumar et al., 2018) possess the rank reversal problem (García and Lamata, 2012; Kong, 2011; Farias and Ferreira, 2019; Senouci et al., 2016). It also helps cloud experts to rate the cloud services in linguistic terms and use it to find the best cloud service. The key components of the framework are discussed below.

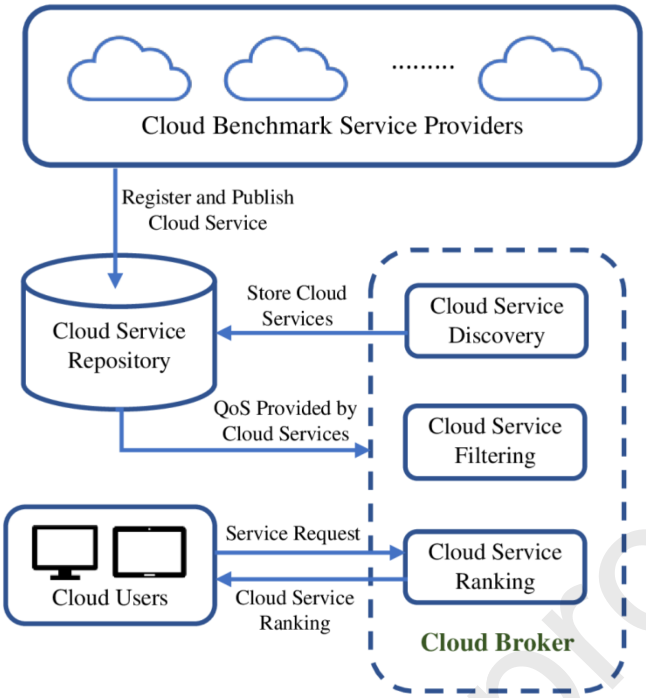

Fig. 2. Proposed Framework for cloud service selection

4.1 Cloud Broker

The cloud broker is the core component of the proposed framework. It performs various tasks like cloud service discovery, cloud service filtering and cloud service ranking that are shown in Figure 2. It also performs billing, identity, and access management. It takes the essential and non-essential QoS parameters as well as their importance from cloud user and interacts with cloud filtering service that filters the cloud services satisfying the cloud user requirements from cloud service repository. The cloud service ranking module of the cloud broker ranks the filtered cloud service as per the importance of each QoS metrics provided by the cloud user. The cloud service ranking module uses the modified N-TOPSIS to find the rank of each cloud service.
The cloud service discovery module of the cloud broker crawls the internet to find the new cloud services existing in the cloud environment and stores them in the cloud service repository. It is like a web crawler which performs the indexing of web pages in the catalog. The cloud filtering service searches the cloud service repository and finds out the cloud services that are providing the services as per the QoS requirement of cloud users.

4.2 Cloud Service Repository

Cloud service repository is a catalog to store information about cloud service providers and QoS parameters provided by them to cloud users for uninterrupted service. It stores the cloud service information for fast access through indexes. The cloud discovery service of the cloud broker discovers the new cloud service from the service advertisement messages of CSPs and accesses the cloud service repository to store them. Cloud benchmark service providers also access cloud service repository to stores the reports, that is used by cloud broker to rank cloud services.

4.3 Cloud Benchmark Service Providers

Cloud benchmark service providers component of the proposed framework continuously test QoS parameters mentioned in service level agreement and publishes cloud services information to cloud service repository. Cloud service providers use cloud benchmark service providers like CloudSpectator (2019), CloudHarmony (2019, etc. to measure their performance statistics. The cloud benchmark service providers test the cloud services in different scenarios at many times by dynamically changing the workload on the cloud. After thorough testing, it computes the performance of cloud services and stores them in the cloud service repository.

Besides the above components, the cloud user is another entity that interacts with the framework and finds the optimal cloud service as per need.

5. Modified N-TOPSIS based Cloud Service Ranking

The proposed framework of cloud service selection in the neutrosophic environment helps the cloud users to find the best CSP as per their needs. The cloud broker component of the proposed framework uses a modified N-TOPSIS method to compute the rank of cloud services and assist cloud users to find optimal cloud service as per their requirements. In this section, we have discussed the schematic framework for cloud service ranking and the detailed procedure involved in it.

The schematic framework used to select the best CSP is shown in Figure 3. It has two main steps-

- Identification of the QoS parameters to find the best cloud service.
- Computation of the rank of cloud services using the modified N-TOPSIS method.

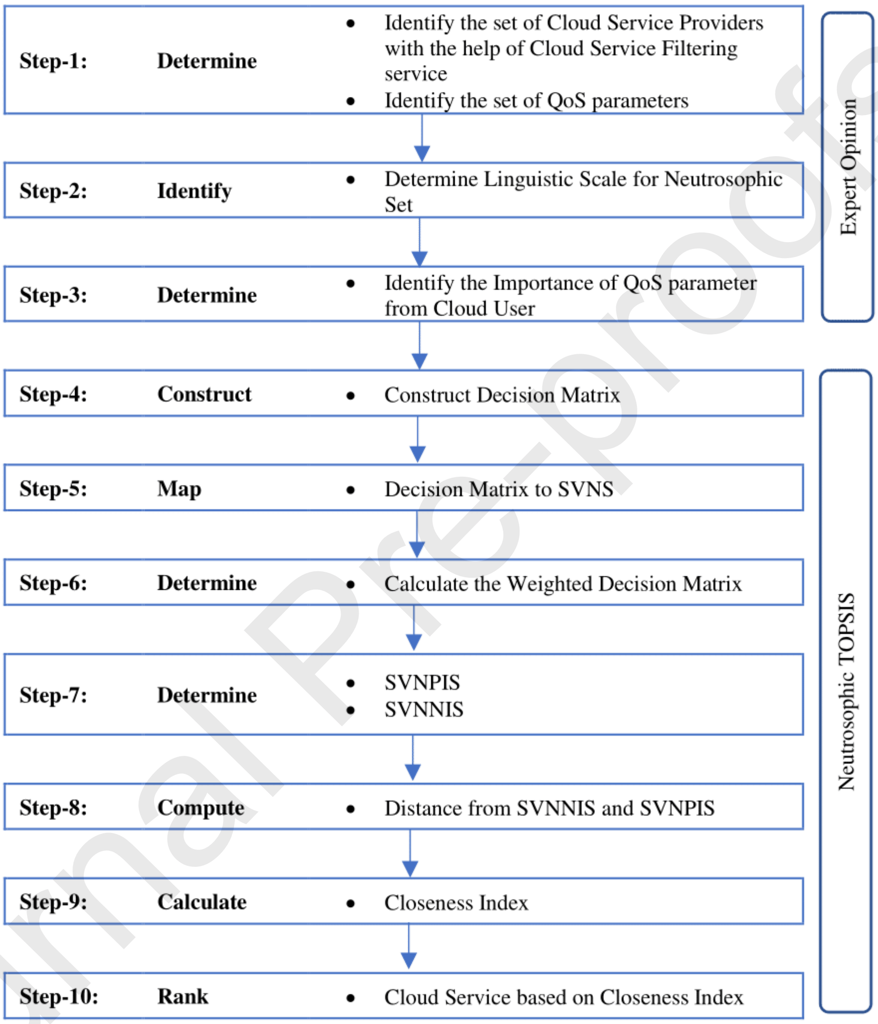

Fig. 3 Schematic framework for cloud service ranking

The first step of cloud service ranking involves the identification of QoS parameters and their importance for selecting the best cloud service. It forms a three-tier hierarchy as shown in Figure 4, where the top layer represents the goal of the cloud service selection. The middle layer represents the criteria or QoS parameters and the bottom layer denotes alternative or CSPs in case of our study. The cloud user determines the QoS parameters and their importance either by himself or with the help of some experts. As our framework is for the neutrosophic environment, so it helps the expert or cloud user to express their opinion in the linguistic term. Once the cloud user provides the set of QoS parameter and their weight, the cloud broker uses a modified N-TOPSIS method to rank the cloud services. The first step of the modified N-TOPSIS method involves the construction of a decision matrix with available cloud services and QoS matrix in linguistic terms. Once the decision matrix is constructed, the linguistic terms are mapped to neutrosophic value with the help of suitable neutrosophic mapping function. The weighted decision matrix is computed by multiplication of the neutrosophic decision matrix and weight vector representing the priority of each QoS parameter. It is computed using Eq. 15. Once the weighted decision matrix is computed, the SVNPIS and SVNNIS are calculated with the help of Eq. 17 and Eq. 18 based on the type of

QoS parameters. The distance of cloud service from SVNNIS and SVNPIS represents how closely the cloud services are as per the QoS requirement of cloud users. The cloud service having the largest distance from SVNNIS and minimum distance from SVNPIS is considered to be the best cloud service. The distance of each cloud service from SVNPIS and SVNNIS is computed using Eq. 19 and Eq. 20. Finally, the closeness index of each cloud service is determined using Eq. 21 and cloud services are ranked as per descending order of closeness index i.e. the cloud service with the highest value of closeness index is ranked best whereas minimum value is ranked worst.

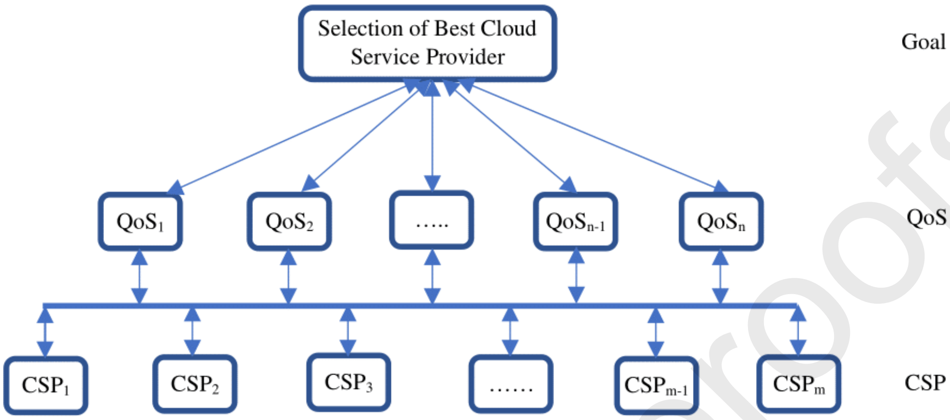

Fig. 4 The three-layer hierarchy for cloud service selection

Algorithm 1 Pseudocode representation of N-TOPSIS for Cloud Service Selection

Input: n: number of Cloud Service Providers, m: number of QoS Parameters
Output: Rank of Cloud Service Providers
1: Input Decision Matrix and Weight of each QoS in Linguistic Term.
2: Convert Decision Matrix and Weight of Each QoS into Neutrosophic Decision Matrix DM and Weight Vector W
3: **for** each $\langle T(x_{i,j}), I(x_{i,j}), F(x_{i,j})\rangle$ in DM **do**
$T_{i,j}^{w} = T(x_{i,j}) * T(w_j)$
$I_{i,j}^{w} = I(x_{i,j}) + I(w_j) - I(x_{i,j}) * I(w_j)$
$F_{i,j}^{w} = F(x_{i,j}) + F(w_j) - F(x_{i,j}) * F(w_j)$
end for
4: Compute
$A^{+} = [\{\langle 1.0,\ 0.0,\ 0.0\rangle\ for\ each\ j \in J_1\}, \{\langle 0.0, 1.0, 1.0\rangle\ for\ each\ j \in J_2\}]$ ▶ J_1Benefit QoS
$A^{-} = [\{\langle 0.0,\ 1.0,\ 1.0\rangle\ for\ each\ j \in J_1\}, \{\langle 1.0, 0.0, 0.0\rangle\ for\ each\ j \in J_2\}]$ ▶ J_2Costly QoS
5: **for** $i=1:n$ **do**
$D_i^{+} = D(A_i, A^{+})$ ▶ $D(A_i, A^{+})$ $as\ per\ Eq.$ 19
$D_i^{-} = D(A_i, A^{-})$ ▶ $D(A_i, A^{-})$ $as\ per\ Eq.$ 20
end for
6: **for** $i=1:n$ **do**
$CI_i = \frac{D_i^{-}}{D_i^{-} + D_i^{+}}$
end for
7: Rank the cloud service providers in descending order of CI_i

The pseudocode representation of modified N-TOPSIS based cloud service ranking is shown in Algorithm 1. The variable *m* and *n* represent the number of CSPs and QoS parameters respectively. The decision-makers input the decision matrix and weight of each criterion in linguistic terms based on the number of CSP and QoS parameters. The linguistic decision matrix and QoS weight vector are converted to neutrosophic decision matrix *DM* and weight vector *W* using a suitable neutrosophic mapping function. The mapping function used in our case study is shown in Table 2. Each element of the neutrosophic decision matrix is represented as $\langle T(x_{i,j}), I(x_{i,j}), F(x_{i,j})\rangle$ in Algorithm 1, where $T(x_{i,j})$, $I(x_{i,j})$ and $F(x_{i,j})$ represent the degree of truth, indeterminacy and falsity respectively for j^{th} QoS parameter of CSP *i*. Similarly, $T(w_j)$, $I(w_j)$ and $F(w_j)$ represents the neutrosophic truth, indeterminacy and falsity weight value of the j^{th} QoS parameter. Based on the neutrosophic decision matrix and weight vector, the weighted neutrosophic decision matrix is computed using neutrosophic set multiplication. $\langle T_{i,j}^{w}, I_{i,j}^{w}, F_{i,j}^{w}\rangle$ in Algorithm 1 represents the truth, indeterminacy and falsity degree of the weighted neutrosophic decision matrix. The SVNPIS A^{+} and SVNNIS A^{-} were computed using weighted neutrosophic decision matrix and type of QoS parameters i.e. cost and benefit parameters. Finally, the distance from SVNPIS and SVNNIS i.e. D_i^{+} and D_i^{-} of each CSP i is computed as shown in Algorithm 1. At last, the closeness index CI_i for each CSP i is computed and CSPs are ranked as per the descending order of closeness index.

6. Case Study

The proposed cloud service selection framework helps cloud user to find the best cloud service as per their requirement. So, a case study is performed on the framework to validate and check its robustness. We have used the real dataset collected by authors of the paper (Kumar et al., 2017) from cloud data servers. They have extracted the dataset from reports published by cloud benchmark service provider *CloudHarmony*. We have performed sensitivity and performance analysis of the framework in addition to its application in cloud service selection. It is also compared and validated with other studies.

6.1 Cloud Service Raking

We have considered ten QoS parameters and six CSPs to demonstrate the working of the proposed framework. The CSPs and QoS parameters used in the case study are shown in Table 1. First four QoS parameters like cost, Network latency, Sequential Disk R/W Performance Consistency and Random Disk R/W Performance Consistency shown in Table 1 are costly whereas CPU Integer Performance, CPU Floating Point Performance, Memory Performance on Scale, Memory Performance on Triad, Sequential R/W Disk Performance and Random R/W Disk Performance are benefit parameters. The scale used by experts to rate the CSPs and the importance of the QoS parameter is given in Table 2. Table 2 also shows the mapping function that maps the linguistic term with neutrosophic value. The various steps involved in cloud service ranking using a modified N-TOPSIS algorithm are discussed below along with numerical calculation for better understanding.

Table 1. Cloud Service Providers and QoS Metrics used in Case Study

Cloud Service Providers	QoS Parameters	
	Costly QoS Parameters	**Benefit QoS Parameters**
SoftLayer	Cost (C)	CPU Integer Performance (CPUIP)
RackSpace	Network Latency (NL)	CPU Floating Point Performance (CPUFPP)
Microsoft Azure	Sequential Disk R/W Performance Consistency (SDRWPC)	Memory Performance on Scale (MPS)
Google	Random Disk R/W Performance Consistency (RDRWPC)	Memory Performance on Triad (MPT)
Digital Ocean		Sequential R/W Disk Performance (SRWDP)
Amazon EC2		Random R/W Disk Performance (RRWDP)

Table 2. Linguistic terms with SVNS value for experts rating

Linguistic terms	SVNS
Extremely High/ Extremely Good (EH/EG)	⟨1.00, 0.00, 0.00⟩
Very High/Very Good (VH/VG)	⟨0.90, 0.10, 0.05⟩
High/Good (H/G)	⟨0.80, 0.20, 0.15⟩
Medium High/ Medium Good (MH/MG)	⟨0.65, 0.35, 0.30⟩
Fair/Medium (F/M)	⟨0.50, 0.50, 0.50⟩
Medium Low/Medium Bad (ML/MB)	⟨0.35, 0.65, 0.60⟩
Low/Bad (L/B)	⟨0.20, 0.75, 0.80⟩
Very Low/Very Bad (VL/VB)	⟨0.10, 0.35, 0.90⟩
Very Very Low/Very Very Bad (VVL/VVB)	⟨0.05, 0.90, 0.95⟩

Step- 1 Construction of Decision Matrix and QoS Weight

The cloud experts construct the decision matrix based on their knowledge. The decision matrix is constructed based on the rating provided by experts on a linguistic term as presented in Table 2. The decision matrix for six CSPs for ten QoS parameters is shown in Table 3. The cloud user identifies the importance of each QoS parameter based on their assessment or with the opinion of cloud experts. The weight of each QoS parameter provided by the cloud user in the linguistic term is shown in Table. 4.

Table 3. Decision matrix with linguistic terms

Cloud Service Providers	C	NL	SDRWPC	RDRWPC	CPUIP	CPUFPP	MPS	MPT	SRWDP	RRWDP
SoftLayer	L	VL	L	F	L	L	H	H	F	F
RackSpace	F	F	F	F	L	L	H	H	H	L
Microsoft Azure	L	F	L	L	VL	VL	F	F	L	L
Google	L	H	L	L	L	L	H	H	VL	VL
Digital Ocean	L	F	VL	VL	L	L	H	H	L	L
Amazon EC2	L	VL	L	L	L	L	H	H	L	L

Table 4. Importance in linguistic term of QoS parameters for cloud service selection

QoS Parameter	C	NL	SDRWPC	RDRWPC	CPUIP	CPUFPP	MPS	MPT	SRWDP	RRWDP
Weight	H	F	VL	L	VH	H	L	F	VL	L

Step- 2 Conversion of Decision Matrix and Weight vector to Neutrosophic set

The neutrosophic set decision matrix is computed using a mapping function shown in Table 2 by converting each linguistic term of decision matrix into neutrosophic value. The mapping function replaces each linguistic term with its corresponding neutrosophic value. For example, the mapping function used in the case study replaces each linguistic term L with ‹0.20, 0.75, 0.80›. Similarly, other linguistic terms based on mapping function are mapped to neutrosophic value and the neutrosophic decision matrix is shown in Table 5. Similarly, the importance given by cloud user in the linguistic term is also converted into neutrosophic value and is shown in Table 6.

Step- 3 Determination of Weighted Neutrosophic Decision Matrix

The weighted neutrosophic decision matrix is computed using the product of the neutrosophic decision matrix and QoS weight vector using Eq. 15. The numerical example to compute truth, indeterminacy and falsity value of an element of the weighted neutrosophic decision matrix is shown in Eq. 22, 23 and 24. The weighted decision matrix is shown in Table 7.

$$T^w_{1,1} = T(x_{1,1}) * T(w_1) = 0.20 * 0.80 = 0.16 \tag{22}$$

$$I^w_{1,1} = I(x_{1,1}) + I(w_1) - I(x_{1,1}) * I(w_1) = 0.75 + 0.20 - 0.75 * 0.20 = 0.80 \tag{23}$$

$$F^w_{1,1} = F(x_{1,1}) + F(w_1) - F(x_{1,1}) * F(w_1) = 0.80 + 0.15 - 0.80 * 0.15 = 0.83 \tag{24}$$

Step- 3 Determination of SVNPIS and SVNNIS

The SVNPIS and SVNNIS are computed using Eq. 17 and 18, respectively. The computed value of SVNNIS and SVNPIS is shown in Table. 8. Since the QoS parameter cost is costly criteria, so the cost element of the SVNPIS vector is computed using Eq. 17 as-

$$A_1^+ = \langle 0.0, 1.0, 1.0\rangle \tag{25}$$

Similarly, for other QoS parameters, SVNPIS and SVNNIS are computed.

Step- 4 Determination of Distance of each CSP from SVNPIS and SVNNIS

The distance of each CSP from SVNPIS and SVNNIS is computed using Eq. 19 and Eq. 20 respectively and is shown in Table 9 considering $\lambda = 1$ and $\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0.25$. Eq. 26 shows the numerical computation of distance of CSP Softlayer from SVNPIS.

$$D_1^+ = \sum_{j=1}^{n} 0.25 * \left(\phi_1(A_{i,j},A_j^+) + \phi_2(A_{i,j},A_j^+) + \phi_3(A_{i,j},A_j^+) + \phi_4(A_{i,j},A_j^+)\right) = 4.7652 \tag{26}$$

Similarly, the distance of each CSP from SVNPIS and SVNNIS is computed.

Step- 5 Determination of Closeness Index of each CSP and Ranking

The closeness index of each CSP is computed using Eq. 21 and its value is shown in Table. 9. At last, the CSPs are ranked based on the value of the closeness index. The CSP with the highest value of the closeness index is ranked first whereas with least value is ranked last.

Table 5. Neutrosophic decision matrix

Cloud Service Providers	C	NL	SDRWPC	RDRWPC	CPUIP	CPUFPP	MPS	MPT	SRWDP	RRWDP
SoftLayer	⟨0.20,0.75,0.80⟩	⟨0.10,0.85,0.90⟩	⟨0.20,0.75,0.80⟩	⟨0.50,0.50,0.45⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩	⟨0.80,0.20,0.15⟩	⟨0.80,0.20,0.15⟩	⟨0.50,0.50,0.45⟩	⟨0.50,0.50,0.45⟩
RackSpace	⟨0.50,0.50,0.45⟩	⟨0.50,0.50,0.45⟩	⟨0.50,0.50,0.45⟩	⟨0.50,0.50,0.45⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩	⟨0.80,0.20,0.15⟩	⟨0.80,0.20,0.15⟩	⟨0.80,0.20,0.15⟩	⟨0.20,0.75,0.80⟩
Microsoft Azure	⟨0.20,0.75,0.80⟩	⟨0.50,0.50,0.45⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩	⟨0.10,0.85,0.90⟩	⟨0.10,0.85,0.90⟩	⟨0.50,0.50,0.45⟩	⟨0.50,0.50,0.45⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩
Google	⟨0.20,0.75,0.80⟩	⟨0.80,0.20,0.15⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩	⟨0.80,0.20,0.15⟩	⟨0.80,0.20,0.15⟩	⟨0.10,0.85,0.90⟩	⟨0.10,0.85,0.90⟩
Digital Ocean	⟨0.20,0.75,0.80⟩	⟨0.50,0.50,0.45⟩	⟨0.10,0.85,0.90⟩	⟨0.10,0.85,0.90⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩	⟨0.80,0.20,0.15⟩	⟨0.80,0.20,0.15⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩
Amazon EC2	⟨0.20,0.75,0.80⟩	⟨0.10,0.85,0.90⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩	⟨0.80,0.20,0.15⟩	⟨0.80,0.20,0.15⟩	⟨0.20,0.75,0.80⟩	⟨0.20,0.75,0.80⟩

Table 6. Neutrosophic weight vector of QoS parameters

C	NL	SDRWPC	RDRWPC	CPUIP	CPUFPP	MPS	MPT	SRWDP	RRWDP
⟨0.80,0.20,0.15⟩	⟨0.50,0.50,0.45⟩	⟨0.10,0.85,0.90⟩	⟨0.20,0.75,0.80⟩	⟨0.90,0.10,0.050⟩	⟨0.80,0.20,0.15⟩	⟨0.20,0.75,0.80⟩	⟨0.50,0.50,0.45⟩	⟨0.10,0.85,0.90⟩	⟨0.20,0.75,0.80⟩

Table 7. Weighted neutrosophic decision matrix

Cloud Service Providers	C	NL	SDRWPC	RDRWPC	CPUIP	CPUFPP	MPS	MPT	SRWDP	RRWDP
SoftLayer	⟨0.1600,0.8000, 0.8300⟩	⟨0.0500,0.9250, 0.9450⟩	⟨0.0200,0.9625, 0.9800⟩	⟨0.1000,0.8750, 0.8900⟩	⟨0.1800,0.7750, 0.8100⟩	⟨0.1600,0.8000, 0.8300⟩	⟨0.1600,0.8000, 0.8300⟩	⟨0.4000,0.6000, 0.5325⟩	⟨0.0500,0.9250, 0.9450⟩	⟨0.1000,0.750, 0.8900⟩
RackSpace	⟨0.4000,0.6000, 0.5325⟩	⟨0.2500,0.7500, 0.6975⟩	⟨0.0500,0.9250, 0.9450⟩	⟨0.1000,0.8750, 0.8900⟩	⟨0.1800,0.7750, 0.8100⟩	⟨0.1600,0.8000, 0.8300⟩	⟨0.1600,0.8000, 0.8300⟩	⟨0.4000,0.6000, 0.5325⟩	⟨0.0800,0.8800, 0.9150⟩	⟨0.0400,0.9375, 0.9600⟩
Microsoft Azure	⟨0.1600,0.8000, 0.8300⟩	⟨0.2500,0.7500, 0.6975⟩	⟨0.0200,0.9625, 0.9800⟩	⟨0.0400,0.9375, 0.9600⟩	⟨0.0900,0.8650, 0.9050⟩	⟨0.0800,0.8800, 0.9150⟩	⟨0.1000,0.8750, 0.8900⟩	⟨0.2500,0.7500, 0.6975⟩	⟨0.0200,0.9625, 0.9800⟩	⟨0.0400,0.9375, 0.9600⟩
Google	⟨0.1600,0.8000, 0.8300⟩	⟨0.4000,0.6000, 0.5325⟩	⟨0.0200,0.9625, 0.9800⟩	⟨0.0400,0.9375, 0.9600⟩	⟨0.1800,0.7750, 0.8100⟩	⟨0.1600,0.8000, 0.8300⟩	⟨0.1600,0.8000, 0.8300⟩	⟨0.4000,0.6000, 0.5325⟩	⟨0.0100,0.9775 ,0.9900⟩	⟨0.0200,0.9625, 0.9800⟩
Digital Ocean	⟨0.1600,0.8000, 0.8300⟩	⟨0.2500,0.7500, 0.6975⟩	⟨0.0100,0.9775, 0.9900⟩	⟨0.0200,0.9625, 0.9800⟩	⟨0.1800,0.7750, 0.8100⟩	⟨0.1600,0.8000, 0.8300⟩	⟨0.1600,0.8000, 0.8300⟩	⟨0.4000,0.6000, 0.5325⟩	⟨0.0200,0.9625, 0.9800⟩	⟨0.0400,0.9375, 0.9600⟩
Amazon EC2	⟨0.1600,0.8000, 0.8300⟩	⟨0.0500,0.9250, 0.9450⟩	⟨0.0200,0.9625, 0.9800⟩	⟨0.0400,0.9375, 0.9600⟩	⟨0.1800,0.7750, 0.8100⟩	⟨0.1600,0.8000, 0.8300⟩	⟨0.1600,0.8000, 0.8300⟩	⟨0.4000,0.6000, 0.5325⟩	⟨0.0200,0.9625, 0.9800⟩	⟨0.0400,0.9375, 0.9600⟩

Table 8. SVNPIS and SVNNIS computed from weighted neutrosophic decision matrix

	C	NL	SDRWPC	RDRWPC	CPUIP	CPUFPP	MPS	MPT	SRWDP	RRWDP
SVNPIS	⟨0.0, 1. 0, 1. 0⟩	⟨0.0, 1. 0, 1. 0⟩	⟨0.0, 1. 0, 1. 0⟩	⟨0.0, 1. 0, 1. 0⟩	⟨1.0, 0.0, 0.0⟩	⟨1.0, 0.0, 0.0⟩	⟨1.0, 0.0, 0.0⟩	⟨1.0, 0.0, 0.0⟩	⟨1.0, 0.0, 0.0⟩	⟨1.0, 0.0, 0.0⟩
SVNNIS	⟨1.0, 0.0, 0.0⟩	⟨1.0, 0.0, 0.0⟩	⟨1.0, 0.0, 0.0⟩	⟨1.0, 0.0, 0.0⟩	⟨0.0, 1. 0, 1. 0⟩	⟨0.0, 1. 0, 1. 0⟩	⟨0.0, 1. 0, 1. 0⟩	⟨0.0, 1. 0, 1. 0⟩	⟨0.0, 1. 0, 1. 0⟩	⟨0.0, 1. 0, 1. 0⟩

.

Table 9. Distance from SVNPIS, SVNNIS, closeness index and rank of each CSP

Cloud Service Providers	D_i^+	D_i^-	***CI***	***Rank***
SoftLayer	5.2348	4.7652	0.4765	1
RackSpace	5.7494	4.2506	0.4251	5
Microsoft Azure	5.8667	4.1333	0.4133	6
Google	5.6623	4.3377	0.4338	4
Digital Ocean	5.4421	4.5579	0.4558	3
Amazon EC2	5.2684	4.7316	0.4732	2

We can observe from the case study that the CSP Softlayer is ranked first whereas Microsoft Azure ranked last. The order of rank of the CSPs is Softlayer, Amazon EC2, Digital Ocean, Google, RackSpace, Microsoft Azure as per the importance of QoS parameters provided by the cloud user.

6.2 Sensitivity and Performance Analysis

A sensitivity analysis is performed to monitor the robustness and consistency of the framework in different scenarios. The main aim of it is to monitor the behavior of the framework with the addition or removal of CSPs and rank reversal problem. Rank reversal problem arises due to change in the number of CSPs i.e. on addition or removal of a CSP. An optimal alternative is ranked to non-optimal on addition or removal of a CSP due to rank reversal problem. We performed sensitivity analysis for two different scenarios.

I. First Case Scenario: Removal of a CSP from the existing cloud services.
II. Second Case Scenario: Addition of a CSP in the existing cloud services.

First Case Scenario

Initially, a sensitivity analysis is performed with the removal of a cloud service from an existing cloud service repository. Six experiments are performed to check the consistency of the framework with the removal of a CSP. In the first experiment, SoftLayer is removed and the rank of other CSPs are computed. RackSpace, Microsoft Azure, Google, Digital Ocean and Amazon EC2 are removed in the specified order in successive experiments like second, third, etc. The closeness index of each CSP is computed in each experiment and is shown in Table 10. The rank of each CSP determined in each experiment is also shown in Figure 5. It can be observed from Figure 5 that SoftLayer always ranked best in each experiment except the experiment when it is removed. Similarly, Microsoft Azure ranked worst in each experiment except when it is not present. It can also be inferred that the rank of each CSP is consistent in each experiment and it changes only when an optimal CSP is removed. So, the proposed framework is robust to rank reversal on removal of a CSP.

Table. 10 Closeness index of CSPs in different experiments in scenario-I

Cloud Service Providers	**Exp.-1**	**Exp.-2**	**Exp.-3**	**Exp.-4**	**Exp.-5**	**Exp.-6**
SoftLayer	--	0.4765	0.4765	0.4765	0.4765	0.4765
RackSpace	0.4251	--	0.4251	0.4251	0.4251	0.4251
Microsoft Azure	0.4133	0.4133	--	0.4133	0.4133	0.4133
Google	0.4338	0.4338	0.4338	--	0.4338	0.4338
Digital Ocean	0.4558	0.4558	0.4558	0.4558	--	0.4558
Amazon EC2	0.4732	0.4732	0.4732	0.4732	0.4732	--

Second Case Scenario

Another case of sensitivity analysis is also performed on the proposed framework with the addition of new CSP in the existing cloud service repository. Initially, SoftLayer and RackSpace are only considered for ranking in the first experiment and their rank is computed. In subsequent experiments, Microsoft Azure, Google, Digital Ocean and Amazon EC2 are added in second, third, fourth and fifth experiments. The rank and closeness index of available CSPs are computed in each experiment. The closeness index is shown in Table 11 and rank in Figure 6. It can be observed from Table 11 that the closeness index of the best CSP always remains consistent and maximum until and unless a new optimal CSP is added to the cloud service repository. Similarly, the same observation can also be inferred from Figure 6. The rank of a cloud service changes in the fifth experiment as an optimal CSP SoftLayer is added with rank one. So, the proposed framework is also robust to rank reversal problem with the addition of a CSP.

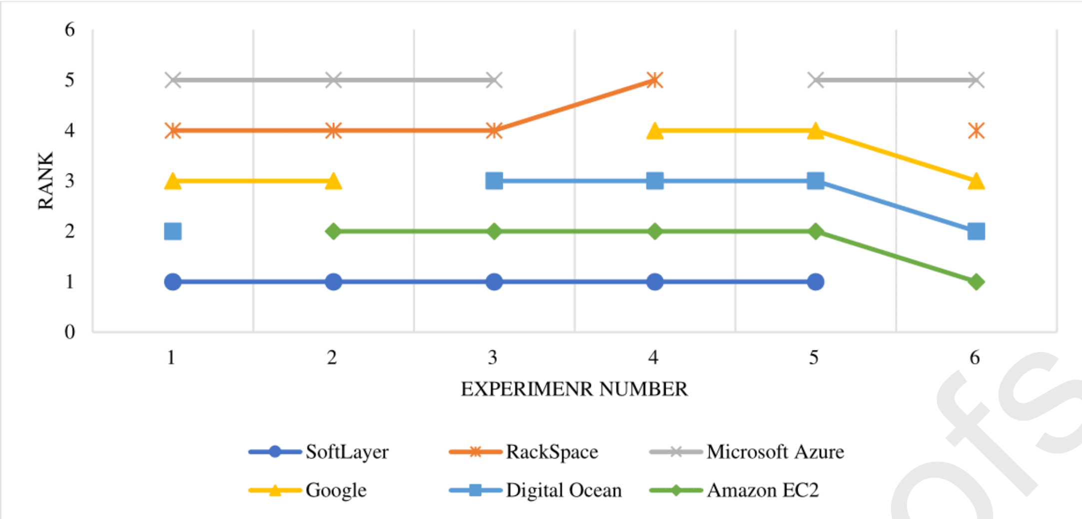

Fig. 5 Rank of CSPs in Different Experiments in Scenario-I

Table. 11 Closeness Index of CSPs in Different experiments in Scenario-II

Cloud Service Providers	**Exp.-1**	**Exp.-2**	**Exp.-3**	**Exp.-4**	**Exp.-5**
SoftLayer	0.4765	0.4765	0.4765	0.4765	0.4765
RackSpace	0.4251	0.4251	0.4251	0.4251	0.4251
Microsoft Azure	--	0.4133	0.4133	0.4133	0.4133
Google	--	--	0.4338	0.4338	0.4338
Digital Ocean	--	--	--	0.4558	0.4558
Amazon EC2	--	--	--	--	0.4732

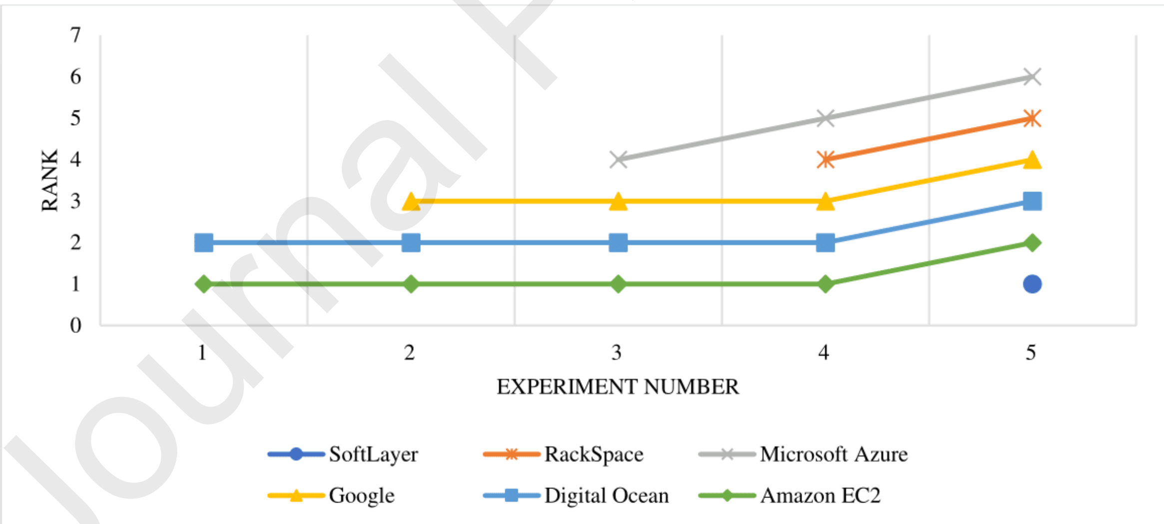

Fig. 6 Rank of CSPs in Different Experiments in Scenario-II

6.3 Result Validation and Discussion

The result obtained in the case study is compared with the existing MCDM based cloud service selection frameworks to validate the correctness and robustness of the framework from the rank reversal problem. The proposed framework is compared with AHP (Garg, et al., 2013), improved TOPSIS (Sidhu and Singh, 2017), Fuzzy TOPSIS (Kumar et al., 2017), N-TOPSIS (Biswas et al., 2016) and neutrosophic VIKOR (Huang et al., 2017) based frameworks. The rank of each CSP obtained in different studies is shown in Table 12. It can be observed from Table 12 that the rank obtained for each CSP in the proposed framework is similar to the Fuzzy TOPSIS, N-TOPSIS and neutrosophic VIKOR based framework while it is very close to rank computed using AHP and improved TOPSIS based frameworks. Figure 7 shows the visual comparison of rank obtained using the proposed framework, N-TOPSIS, neutrosophic VIKOR, AHP, improved TOPSIS and Fuzzy TOPSIS. So, it can be inferred that the proposed framework is consistent with cloud service selection frameworks based on TOPSIS and other MCDM methods.

Table 12. The rank order of CSPs with other MCDM based frameworks

MCDM Method based Framework	Rank
Proposed Framework	Microsoft Azure < RackSpace < Google < Digital Ocean < Amazon EC2 < SoftLayer
Neutrosophic VIKOR (Huang et al., 2017)	Microsoft Azure < RackSpace < Google < Digital Ocean < SoftLayer < Amazon EC2
Neutrosophic TOPSIS (Biswas et al., 2016)	Microsoft Azure < RackSpace < Google < Digital Ocean < Amazon EC2 < SoftLayer
Fuzzy TOPSIS (Kumar et al., 2017)	Microsoft Azure < RackSpace < Google < Digital Ocean < Amazon EC2 < SoftLayer
AHP (Garg at al., 2013)	Digital Ocean < Microsoft Azure < Google < RackSpace < SoftLayer < Amazon EC2
Improved TOPSIS (Sidhu and Singh, 2017)	Google < Microsoft Azure < RackSpace < Digital Ocean < Amazon EC2 < SoftLayer

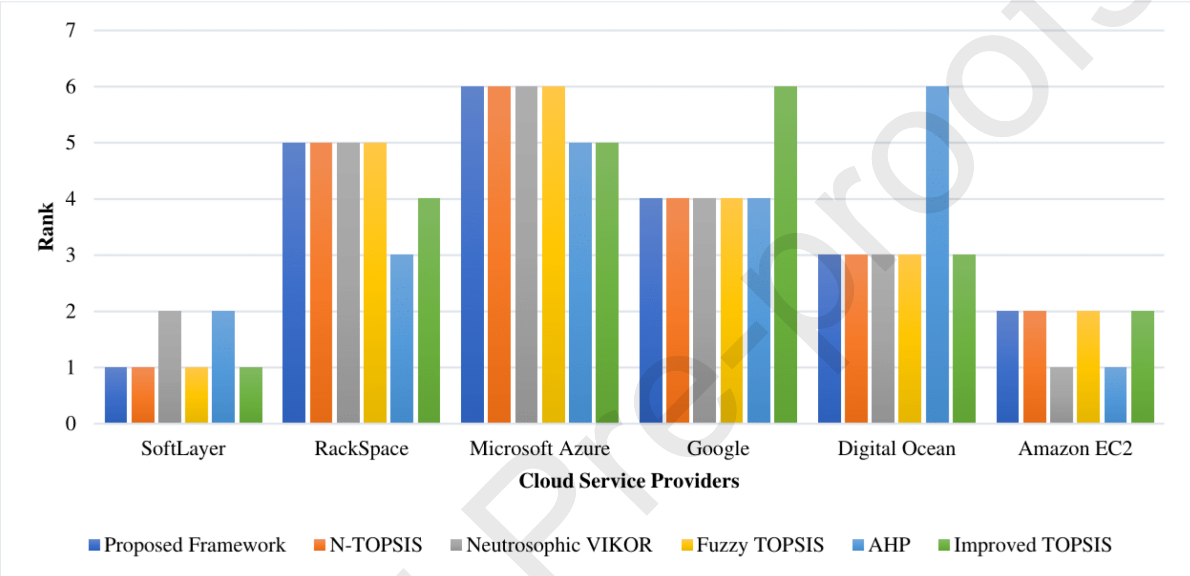

Fig. 8 Rank comparison of CSPs with other MCDM based frameworks

The proposed framework is also compared with other MCDM based frameworks mentioned above in terms of their robustness from rank reversal and vagueness. The cloud service selection framework based on AHP (Garg at al., 2013) works only for the crisp environment and suffers from rank reversal problem as many studies have proved that ordinary AHP (Saaty, 1990) suffers from rank reversal. The improved TOPSIS framework (Sidhu and Singh, 2017) is also not robust from rank reversal as it is based on the original TOPSIS method which suffers from rank reversal (García Cascales et al., 2012) and works only in the crisp environment. The cloud service selection frameworks based on fuzzy TOPSIS (Kumar et al., 2017) is robust to rank reversal but has limited capability to handle the vagueness as it works for the ordinary fuzzy environment, where each element has only membership value, whereas the proposed framework is robust to rank reversal problem which is verified from the sensitivity analysis. The neutrosophic TOPSIS (Biswas et al., 2016) works strongly in the fuzzy environment and robust to rank reversal but the closeness index value a CSP changes with the addition or removal of a CSP which may lead inconsistency. The neutrosophic VIKOR also handles a fuzzy environment strongly and robust to rank reversal. The proposed framework also provides more flexibility to decision-makers as it works in a neutrosophic environment where they can express their opinion in terms of truth, indeterminacy and falsity. So, the proposed framework offers more flexibility to decision-makers in an uncertain environment. Table 13 shows the comparison of the proposed framework with other studies discussed above in terms of rank reversal robustness and capability to work in a fuzzy environment.

The performance of the proposed framework is also compared with neutrosophic TOPSIS and VIKOR. The performance is evaluated on a system with Intel core i7 processor, 4GB RAM and Windows 8 64-bit operating system. We randomly generated linguistic terms for 1500 CSPs for ten QoS parameters mentioned in Table 1. Initially, we ran the framework for 100 CSPs and measured the elapsed time. Subsequently, we linearly increased the number of CSPs and measured the time elapsed in each iteration. Figure 8 shows the execution time of the proposed framework along with neutrosophic TOPSIS and VIKOR with a varying number of CSPs. It can be inferred from Figure 8 that the execution time of the proposed framework has a linear relationship with the number of CSPs and more efficient than neutrosophic TOPSIS and VIKOR.

Table 13. Comparison of the proposed framework with other cloud service selection frameworks

MCDM Method based Framework	Rank Reversal Robustness	Fuzzy Capability
Proposed Framework	Yes	Strong
Neutrosophic VIKOR (Huang et al., 2017)	Yes	Strong
Neutrosophic TOPSIS (Biswas et al., 2016)	Yes	Strong
Fuzzy TOPSIS (Kumar et al., 2017)	Yes	Limited
AHP (Garg at al., 2013)	No	No
Improved TOPSIS (Sidhu and Singh, 2017)	No	No

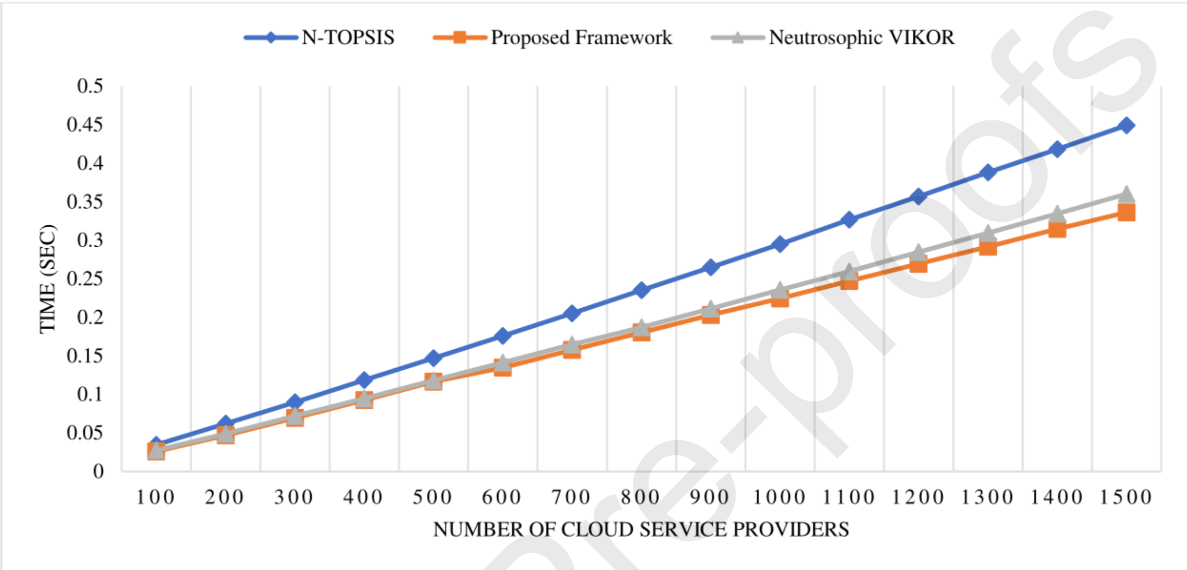

Fig. 8 Execution time analysis with the number of CSPs

7. Conclusions and Future Directions

Cloud computing has disrupted the business model in the current era. Due to its high demand by customers and an increasing number of cloud service offering organizations, it has become a challenge to choose the right service provider for the right task. In this paper, a cloud service selection framework has been designed to assist the cloud users and experts in the neutrosophic environment. It helps cloud users to find the best cloud service as per their functional and non-functional requirements by the linguistic rating of cloud services with partial or imprecise knowledge, which reduces the chances of huge loss in long run. The frameworks available in the literature for cloud service selection for imprecise linguistic rating uses ordinary fuzzy set theory which has only a membership degree. The proposed framework uses a combination of SVNS with the MCDM method TOPSIS to develop a modified N-TOPSIS, which is used to select the right service provider. It uses SVNS to handle the imprecise knowledge involving three dimensions- degree of truth, indeterminacy and falsehood for the first time in literature while modified N-TOPSIS selects the best cloud service efficiently. The proposed framework is validated on a real dataset obtained from reports published by CloudHarmony.

The proposed framework is exhaustively validated and tested using sensitivity analysis. Sensitivity analysis is performed to check the correctness and efficacy of the framework from rank reversal problem. The sensitivity analysis performed with the addition and deletion of a CSP suggests that the framework is stable with the addition or deletion of CSPs and robust to rank reversal phenomenon. The proposed framework is also compared with the frameworks available in the literature and found that it ranks CSPs similar to them and strongly capable to handle a fuzzy environment along with robustness from rank reversal. The framework also performs more efficiently than other neutrosophic methods. Overall, the proposed framework is robust and consistent for cloud service selection.

In the future, it can be extended for group decision making in cloud service selection and can be integrated with other MCDM methods to make it more efficient. It can also be extended to interval-valued neutrosophic set or can be integrated with rough set theory to handle vagueness more strongly.

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