Entropy Measure on Selection of Cloud Computing using Bipolar Neutrosophic Environment Utilizing Topsis Method

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Abstract

Multi-criteria decision-making is essential for resolving issues in the real world. The choice of cloud computing services on the basis of service quality is solved in this paper using bipolar-neutrosophic circumstances. The removal area approach is used to carry out the de-bipolarization technique. The results have been compared with other methods found in the research to determine which method provides better cloud service.

Keywords: Neutrosophic set; Bipolar Neutrosophic set; cloud computing; TOPSIS; De-Bipolarization

1. Introduction

Because the cloud service provider's wide range of applications allows businesses to invest significant resources in its development, it has evolved into a necessary tool for work in our daily lives. Three distinct types of cloud services are available: software as a service (SaaS), platform as a service (PaaS), and infrastructure as a service (IaaS). Big businesses like Amazon, Google, IBM, and others are the market leaders, and this service is based on subscriptions, though not in that order. Cloud computing offers businesses, workspaces, and educational institutions many benefits at a minimal cost of ownership. The market for CSPs is growing exponentially, making it harder for customers to decide which CSP best suits their demands and specifications. As a result, customers can now select the most effective CSP on the basis of quality of service, which makes it easier for cloud users to make this decision. The cloud user uses a simple method to determine which CSP is best, according to the cloud measurement service suppliers analysis released by CloudSpheral2019, CloudHarmony2019, which analyzes the cloud's latency among other performance metrics. In accordance with the assessment of the Cloud Service Measurement Initiative Consortium (CSMIC), which has discovered several measurements for QoS factors, the rightest CSP is chosen using a variety of criteria. The process of choosing the optimal CSP for the given alternatives and attributes based on a multi-criteria choice-making problem using an ordering method. The authors have researched a number of MCDM techniques, including the fuzzy AHP, fuzzy TOPSIS, ELECTRE. The fuzzy set theory aids in decision-making by providing administrators and cloud users with linguistic terms to express their views, which have been assigned to membership values.

2. Review of Literature

In 1986, (Atanassov) established the intuitionistic fuzzy set. Generalized triangular neutrosophic numbers, both linear and non-linear, which are important for understanding ambiguity. For triangular neutrosophic numbers, the idea of de-neutrosophication was introduced. The conversion of a neutrosophic number into a crisp number is made easier by this concept. This study presented the route selection problem [3] this research created a cloud service choice methodology for the neutrosophic context utilizing multi-criteria choice making based technique. To prove the applicability and usefulness of Cloud Harmony, an instance study with an actual dataset

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was conducted. The sensitivity evaluation was used to rate cloud services based on their additions and deletions, and it was discovered that this structure is accurate and uniform for ranking reversal problems. [4] Fuzzy logic was utilized to determine durability in a cloud computing context. The user input part made advantage of efficiency, flexibility, and rapidity of the processor. In the resultant part, the system's durability has been demonstrated using the system that is unclear. The main goal was to increase the cloud's technological durability. [5] The TOPSIS technique finds the answer that is the adjacent to the perfect answer and the furthest from the undesirable-perfect answer, but the problem doesn't take into account how important these variations are in relation to one another. A mathematical illustration is provided to demonstrate a comparative comparison of these two methodologies.[6] The paper shows how successfully crisp pictures and pictures with varying amount of noise may be segmented using neutrosophic classification. Based on findings, it can be concluded that the suggested method produces the best partitioned picture for removing features, which is useful for creating effective databases. [7] The suggested approach evaluates each criterion score by using a collection of established linguistic parameters that are characterized by triangle numbers that are unclear. When contrasted with additional accessible cloud provider choice computations, the test outcomes produced utilizing the current cloud provider categories indicate the usefulness of our suggested approach and establish it's effective by causing greater efficiency. Ultimately, it is convinced that the accuracy of the assessment validates the resilience of our suggested paradigm. [8]To illustrate its applicability and efficiency, an experiment with an actual information from CloudHarmony was recently conducted. A sensitivity evaluation was used to rate cloud providers based on their additions and deletions, which means it was discovered how the structure is accurate and reliable for ranking reversal problems. Compared to other MCDM-based cloud platform choice approaches that are accessible in the research, this system is also capable to manage an uncertain setting with strength without exhibiting position inversion phenomena. [9] The suggested framework's application and usefulness have been demonstrated through the use of an actual study-based methodology. Real cloud information taken from actual Cloud Integration indicates has been used for the research. It is evident from the findings of the study that the suggested approach, which makes use of actual time cloud evaluation, may be applied in actual cloud settings to assess the reliability of the service suppliers [10]. To rate the significance of requirements and possibilities, the opinions of every possible making the choice are combined into one overall view using a multi-valued neutrosophic set-based generalized aggregating function. Ultimately, an exemplary scenario is shown to showcase the value and practicality of the suggested methodology [12]. In this study, we suggest a methodology and a structure for ranking and evaluating cloud computing services. A system like this can have a big influence and encourage competitiveness across cloud service suppliers, allowing them to better their Quality of Service and collect their Facility Point Arrangements. Employing a case investigation, we have demonstrated the order of importance framework's usefulness [13]. Attribute levels are acquired by the greatest deviations technique. To be able to test the feasibility and logic of the proposed framework with undetermined weights for variables in the situation, we lastly run the produced MADM modelling for a TQE instance and contrast it against other suitable models that already available.[14] Depending on the suggested assess, an algorithm that recognizes patterns is created, and computational analyses are used to show that the suggested threshold minimizes the limits of existing techniques. By aligning the items on the various levels of trust, the clustering method significantly assesses the effectiveness of the proposed measure. Ultimately, an innovative method for making decisions is created using the proposed measure, and its reliability is confirmed through a comparison analysis with the current technique. [15] The use of the image of the fuzzy soft graph in the present COVID paradigm to apply making choices towards medical classification has been demonstrated.[16] The investigation found that not every facets of threat evaluation and protection assaults were included in previous works. Additionally, hazard factors that have not been thoroughly discussed in earlier publications are understood, categorized, valued, and promoted. A summary of the architectural cloud offensive and hazards framework is given in this work.[17] Public involvement, invention of technologies, creativity organizing, and invention monitoring are the four categories of remedies identified by the framework, which also includes the following types of dangers information technology, interpret, and solutions. Moreover, executives can use the framework to determine the overall risk rating of the firm and connect the profile to a particular set of remedies.[18] In comparison to current techniques, the suggested model is thought to be reliable and accurate in dealing with and expressing ambiguity and partial danger data utilizing neutrosophic sets.[19]

3. Preliminaries

In this section basic definitions of neutrosophic set has been discussed

3.1. Bipolar Neutrosophic set

An object with a structure of the for $A = \{< x, T_A^+(x), I_A^+(x), F_A^+(x), T_A^-(x), I_A^-(x), F_A^-(x) >: x \in X\}$ is referred to as a bipolar Neutrosophic set A in X. where the positive membership degree $T_A^+(x), I_A^+(x), F_A^+(x)$ denote the truth membership function, indeterminacy membership function, falsity membership function of an element $x \in X$. Corresponding to a bipolar Neutrosophic set A the negative

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membership degree $T_A^-(x), I_A^-(x), F_A^-(x)$ denote the truth membership, Indeterminacy membership, Falsity membership functions.

3.2. Single Valued Bipolar Dodecagonal Neutrosophic Number (SVBDONN)

Single valued Bipolar Dodecagonal Neutrosophic Number is defined as

$$\text{SVB}\widetilde{\text{DoNN}} =< \begin{pmatrix} \gamma_1,\gamma_2,\gamma_3,\gamma_4,\gamma_5,\gamma_6,\gamma_7,\gamma_8,\gamma_9,\gamma_{10},\gamma_{11},\gamma_{12}; \\ \mu_1,\mu_2,\mu_3,\mu_4,\mu_5,\mu_6,\mu_7,\mu_8,\mu_9,\mu_{10},\mu_{11},\mu_{12}; \\ \vartheta_1,\vartheta_2,\vartheta_3,\vartheta_4,\vartheta_5,\vartheta_6,\vartheta_7,\vartheta_8,\vartheta_9,\vartheta_{10},\vartheta_{11},\vartheta_{12} \end{pmatrix}$$
$$\begin{pmatrix} -\gamma_1,-\gamma_2,-\gamma_3,-\gamma_4,-\gamma_5,-\gamma_6,-\gamma_7,-\gamma_8,-\gamma_9,-\gamma_{10},-\gamma_{11},-\gamma_{12}; \\ -\mu_1,-\mu_2,-\mu_3,-\mu_4,-\mu_5,-\mu_6,-\mu_7,-\mu_8,-\mu_9,-\mu_{10},-\mu_{11},-\mu_{12}; \\ -\vartheta_1,-\vartheta_2,-\vartheta_3,-\vartheta_4,-\vartheta_5,-\vartheta_6,-\vartheta_7,-\vartheta_8,-\vartheta_9,-\vartheta_{10},-\vartheta_{11},-\vartheta_{12} \end{pmatrix} >$$

Where truth membership function, Indeterminate membership function and falsity membership functions respectively.

Truth membership function

$T^+_{\text{SVB}\widetilde{\text{DoNN}}}(x): X \to [0,1]$

$T^-_{\text{SVB}\widetilde{\text{DoNN}}}(x): X \to [-1,0]$

$where\ X$ is a universe of discourse

$$-1 \le \sup\{T^+_{\text{SVB}\widetilde{\text{DoNN}}}(x)\} + \sup\{T^-_{\text{SVB}\widetilde{\text{DoNN}}}(x)\} \le 1$$

$$T^+_{\text{SVB}\widetilde{\text{DoNN}}}(x) = \begin{cases} \left(\frac{x-\tau_1}{\tau_2-\tau_1}\right) & if\ \tau_1 \le x \le \tau_2 \\ \left(\frac{x-\tau_2}{\tau_3-\tau_2}\right) & if\ \tau_2 \le x \le \tau_3 \\ \left(\frac{x-\tau_3}{\tau_4-\tau_3}\right) & if\ \tau_3 \le x \le \tau_4 \\ \left(\frac{x-\tau_4}{\tau_5-\tau_4}\right) & if\ \tau_4 \le x \le \tau_5 \\ \left(\frac{x-\tau_5}{\tau_6-\tau_5}\right) & if\ \tau_5 \le x \le \tau_6 \\ 1 & if\ x = \tau_6 \\ 1 & if\ x = \tau_7 \\ \left(\frac{\tau_8-x}{\tau_8-\tau_7}\right) & if\ \tau_7 \le x \le \tau_8 \\ \left(\frac{\tau_9-x}{\tau_9-\tau_8}\right) & if\ \tau_8 \le x \le \tau_9 \\ \left(\frac{\tau_{10}-x}{\tau_{10}-\tau_9}\right) & if\ \tau_9 \le x \le \tau_{10} \\ \left(\frac{\tau_{11}-x}{\tau_{11}-\tau_{10}}\right) & if\ \tau_{10} \le x \le \tau_{11} \\ \left(\frac{\tau_{12}-x}{\tau_{12}-\tau_{11}}\right) & if\ \tau_{11} \le x \le \tau_{12} \\ 0 & otherwise \end{cases}$$

$$T^-_{\text{SVB}\widetilde{\text{DoNN}}}(x) = \begin{cases} \left(\frac{\tau_2-x}{\tau_2-\tau_1}\right) & if\ \tau_1 \le x \le \tau_2 \\ \left(\frac{\tau_3-x}{\tau_3-\tau_2}\right) & if\ \tau_2 \le x \le \tau_3 \\ \left(\frac{\tau_4-x}{\tau_4-\tau_3}\right) & if\ \tau_3 \le x \le \tau_4 \\ \left(\frac{\tau_5-x}{\tau_5-\tau_4}\right) & if\ \tau_4 \le x \le \tau_5 \\ \left(\frac{\tau_6-x}{\tau_6-\tau_5}\right) & if\ \tau_5 \le x \le \tau_6 \\ -1 & if\ x = \tau_6 \\ -1 & if\ x = \tau_7 \\ \left(\frac{x-\tau_8}{\tau_8-\tau_7}\right) & if\ \tau_7 \le x \le \tau_8 \\ \left(\frac{x-\tau_9}{\tau_9-\tau_8}\right) & if\ \tau_8 \le x \le \tau_9 \\ \left(\frac{x-\tau_{10}}{\tau_{10}-\tau_9}\right) & if\ \tau_9 \le x \le \tau_{10} \\ \left(\frac{x-\tau_{11}}{\tau_{11}-\tau_{10}}\right) & if\ \tau_{10} \le x \le \tau_{11} \\ \left(\frac{x-\tau_{12}}{\tau_{12}-\tau_{11}}\right) & if\ \tau_{11} \le x \le \tau_{12} \\ 0 & otherwise \end{cases}$$

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Indeterminacy membership function

$I^{+}_{\mathrm{SV\widetilde{BDoNN}}}(x): X \to [0,1]$
$I^{-}_{\mathrm{SV\widetilde{BDoNN}}}(x): X \to [-1,0]$

$where\ X$ is a universe of discourse

$$-1 \le \sup\{I^{+}_{\mathrm{SV\widetilde{BDoNN}}}(x)\} + \sup\{I^{-}_{\mathrm{SV\widetilde{BDoNN}}}(x)\} \le 1$$

$$I^{+}_{\mathrm{SV\widetilde{BDoNN}}}(x) = \begin{cases} \left(\frac{\phi_2 - x}{\phi_2 - \phi_1}\right) & if\ \phi_1 \le x \le \phi_2 \\ \left(\frac{\phi_3 - x}{\phi_3 - \phi_2}\right) & if\ \phi_2 \le x \le \phi_3 \\ \left(\frac{\phi_4 - x}{\phi_4 - \phi_3}\right) & if\ \phi_3 \le x \le \phi_4 \\ \left(\frac{\phi_5 - x}{\phi_5 - \phi_4}\right) & if\ \phi_4 \le x \le \phi_5 \\ \left(\frac{\phi_6 - x}{\phi_6 - \phi_5}\right) & if\ \phi_5 \le x \le \phi_6 \\ 0 & if\ x = \phi_6 \\ 0 & if\ x = \phi_7 \\ \left(\frac{x - \phi_8}{\phi_8 - \phi_7}\right) & if\ \phi_7 \le x \le \phi_8 \\ \left(\frac{x - \phi_9}{\phi_9 - \phi_8}\right) & if\ \phi_8 \le x \le \phi_9 \\ \left(\frac{x - \phi_{10}}{\phi_{10} - \phi_9}\right) & if\ \phi_9 \le x \le \phi_{10} \\ \left(\frac{x - \phi_{11}}{\phi_{11} - \phi_{10}}\right) & if\ \phi_{10} \le x \le \phi_{11} \\ \left(\frac{x - \phi_{12}}{\phi_{12} - \phi_{11}}\right) & if\ \phi_{11} \le x \le \phi_{12} \\ 1 & otherwise \end{cases}
\quad
I^{-}_{\mathrm{SV\widetilde{BDoNN}}}(x) = \begin{cases} \left(\frac{x - \phi_1}{\phi_2 - \phi_1}\right) & if\ \phi_1 \le x \le \phi_2 \\ \left(\frac{x - \phi_2}{\phi_3 - \phi_2}\right) & if\ \phi_2 \le x \le \phi_3 \\ \left(\frac{x - \phi_3}{\phi_4 - \phi_3}\right) & if\ \phi_3 \le x \le \phi_4 \\ \left(\frac{x - \phi_4}{\phi_5 - \phi_4}\right) & if\ \phi_4 \le x \le \phi_5 \\ \left(\frac{x - \phi_5}{\phi_6 - \phi_5}\right) & if\ \phi_5 \le x \le \phi_6 \\ 0 & if\ x = \phi_6 \\ 0 & if\ x = \phi_7 \\ \left(\frac{\phi_8 - x}{\phi_8 - \phi_7}\right) & if\ \phi_7 \le x \le \phi_8 \\ \left(\frac{\phi_9 - x}{\phi_9 - \phi_8}\right) & if\ \phi_8 \le x \le \phi_9 \\ \left(\frac{\phi_{10} - x}{\phi_{10} - \phi_9}\right) & if\ \phi_9 \le x \le \phi_{10} \\ \left(\frac{\phi_{11} - x}{\phi_{11} - \phi_{10}}\right) & if\ \phi_{10} \le x \le \phi_{11} \\ \left(\frac{\phi_{12} - x}{\phi_{12} - \phi_{11}}\right) & if\ \phi_{11} \le x \le \phi_{12} \\ -1 & otherwise \end{cases}$$

Falsity membership function

$F^{+}_{\mathrm{SV\widetilde{BDoNN}}}(x): X \to [0,1]$
$F^{-}_{\mathrm{SV\widetilde{BDoNN}}}(x): X \to [-1,0]$

$where\ X$ is a universe of discourse

$$-1 \le \sup\{F^{+}_{\mathrm{SV\widetilde{BDoNN}}}(x)\} + \sup\{F^{-}_{\mathrm{SV\widetilde{BDoNN}}}(x)\} \le 1$$

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$$F^{+}_{\mathrm{SVB\widetilde{DO}NN}}(x)=\begin{cases}\left(\frac{\omega_2-x}{\omega_2-\omega_1}\right) & if\ \omega_1\le x\le\omega_2\\ \left(\frac{\omega_3-x}{\omega_3-\omega_2}\right) & if\ \omega_2\le x\le\omega_3\\ \left(\frac{\omega_4-x}{\omega_4-\omega_3}\right) & if\ \omega_3\le x\le\omega_4\\ \left(\frac{\omega_5-x}{\omega_5-\omega_4}\right) & if\ \omega_4\le x\le\omega_5\\ \left(\frac{\omega_6-x}{\omega_6-\omega_5}\right) & if\ \omega_5\le x\le\omega_6\\ 0 & if\ x=\omega_6\\ 0 & if\ x=\omega_7\\ \left(\frac{x-\omega_8}{\omega_8-\omega_7}\right) & if\ \omega_7\le x\le\omega_8\\ \left(\frac{x-\omega_9}{\omega_9-\omega_8}\right) & if\ \omega_8\le x\le\omega_9\\ \left(\frac{x-\omega_{10}}{\omega_{10}-\omega_9}\right) & if\ \omega_9\le x\le\omega_{10}\\ \left(\frac{x-\omega_{11}}{\omega_{11}-\omega_{10}}\right) & if\ \omega_{10}\le x\le\omega_{11}\\ \left(\frac{x-\omega_{12}}{\omega_{12}-\omega_{11}}\right) & if\ \omega_{11}\le x\le\omega_{12}\\ 1 & otherwise\end{cases}$$

$$F^{-}_{\mathrm{SVB\widetilde{DO}NN}}(x)=\begin{cases}\left(\frac{x-\omega_1}{\omega_2-\omega_1}\right) & if\ \omega_1\le x\le\omega_2\\ \left(\frac{x-\omega_2}{\omega_3-\omega_2}\right) & if\ \omega_2\le x\le\omega_3\\ \left(\frac{x-\omega_3}{\omega_4-\omega_3}\right) & if\ \omega_3\le x\le\omega_4\\ \left(\frac{x-\omega_4}{\omega_5-\omega_4}\right) & if\ \omega_4\le x\le\omega_5\\ \left(\frac{x-\omega_5}{\omega_6-\omega_5}\right) & if\ \omega_5\le x\le\omega_6\\ 0 & if\ x=\omega_6\\ 0 & if\ x=\omega_7\\ \left(\frac{\omega_8-x}{\omega_8-\omega_7}\right) & if\ \omega_7\le x\le\omega_8\\ \left(\frac{\omega_9-x}{\omega_9-\omega_8}\right) & if\ \omega_8\le x\le\omega_9\\ \left(\frac{\omega_{10}-x}{\omega_{10}-\omega_9}\right) & if\ \omega_9\le x\le\omega_{10}\\ \left(\frac{\omega_{11}-x}{\omega_{11}-\omega_{10}}\right) & if\ \omega_{10}\le x\le\omega_{11}\\ \left(\frac{\omega_{12}-x}{\omega_{12}-\omega_{11}}\right) & if\ \omega_{11}\le x\le\omega_{12}\\ -1 & otherwise\end{cases}$$

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$$where\ {}^{-}3 \leq T_{\mathrm{SV\widetilde{BDo}NN}}(x) + I_{\mathrm{SV\widetilde{BDo}NN}}(x) + F_{\mathrm{SV\widetilde{BDo}NN}}(x) \leq 3^{+}$$

Graphical Representation of SVBDoNN

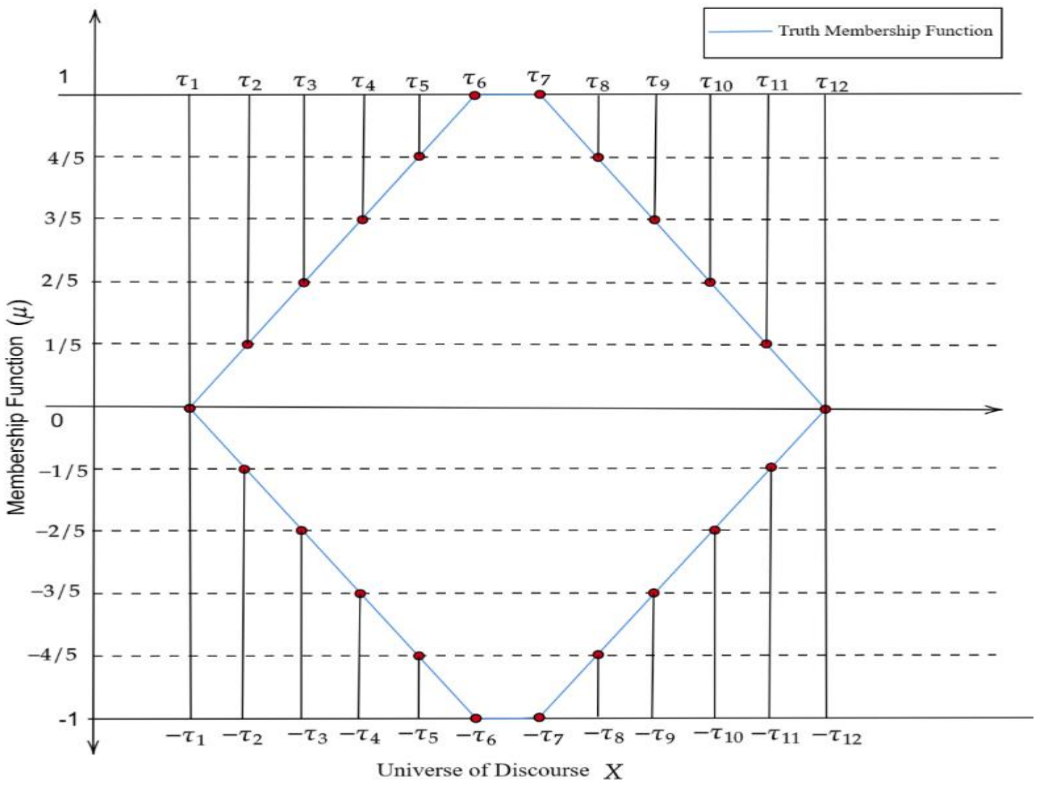

Figure 1. Truth membership function of SVBDoNN

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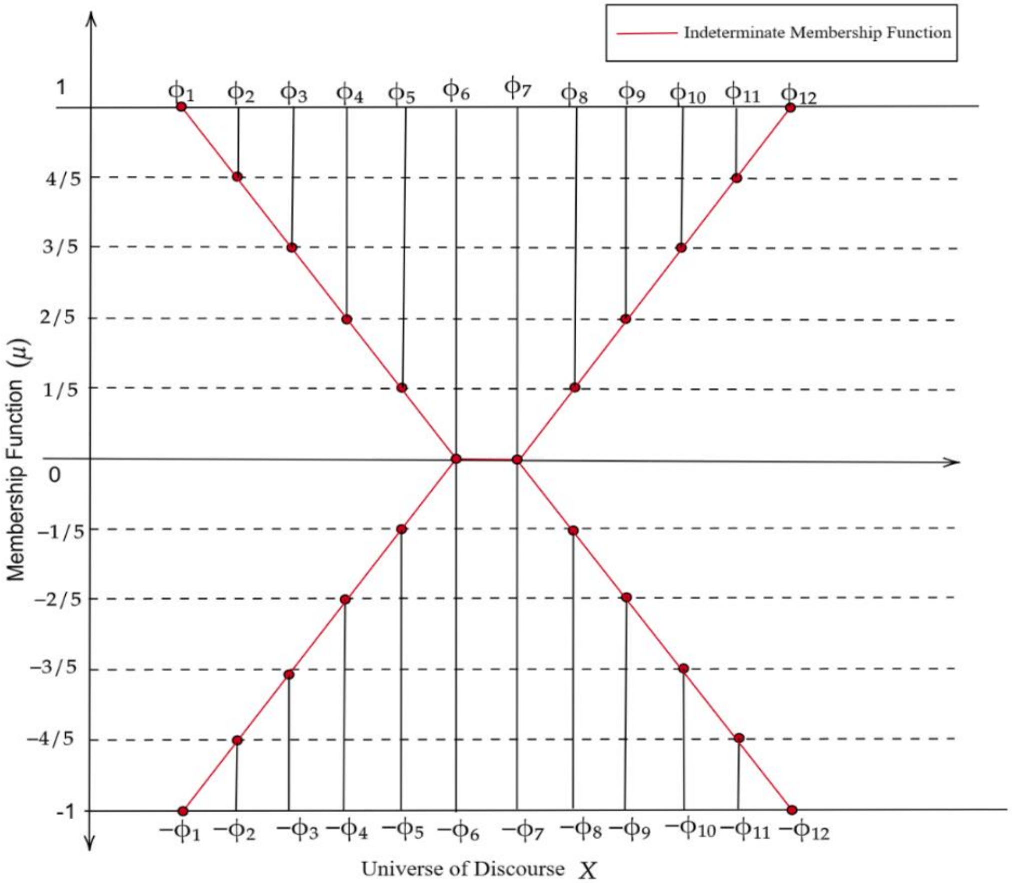

Figure 1. Indeterminate membership function of SVBDoNN

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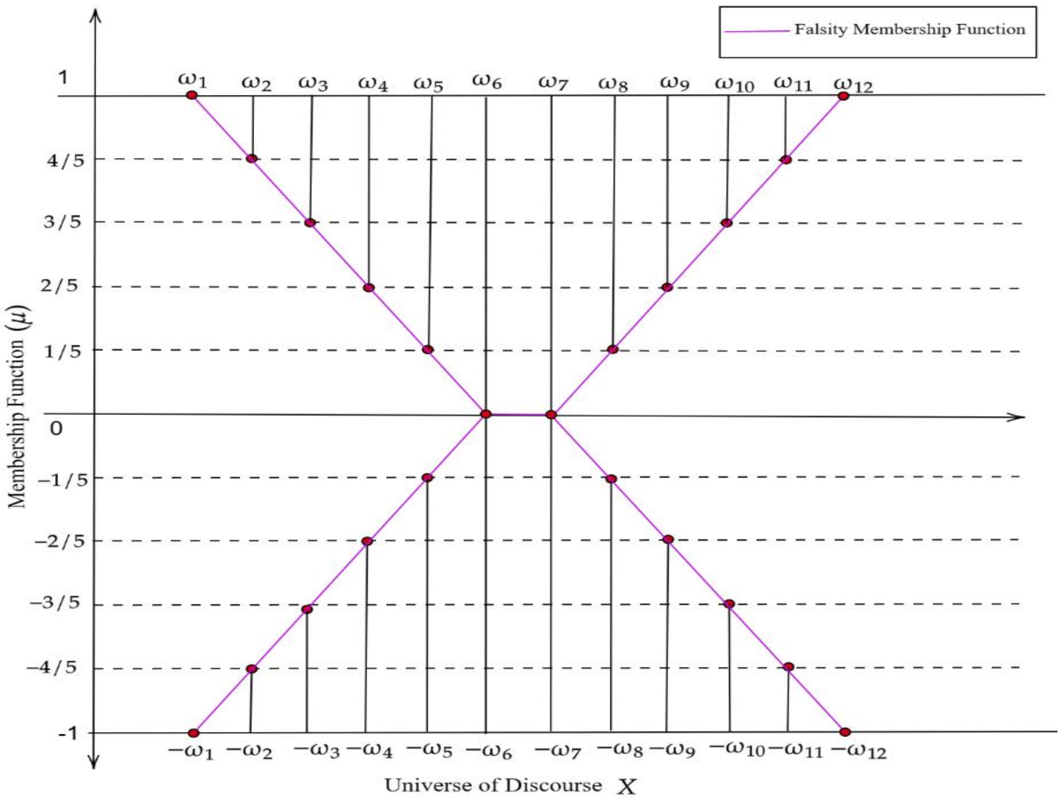

Figure 2. Falsity membership function of SVBDoNN

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De-Bipolarization of the Proposed Number

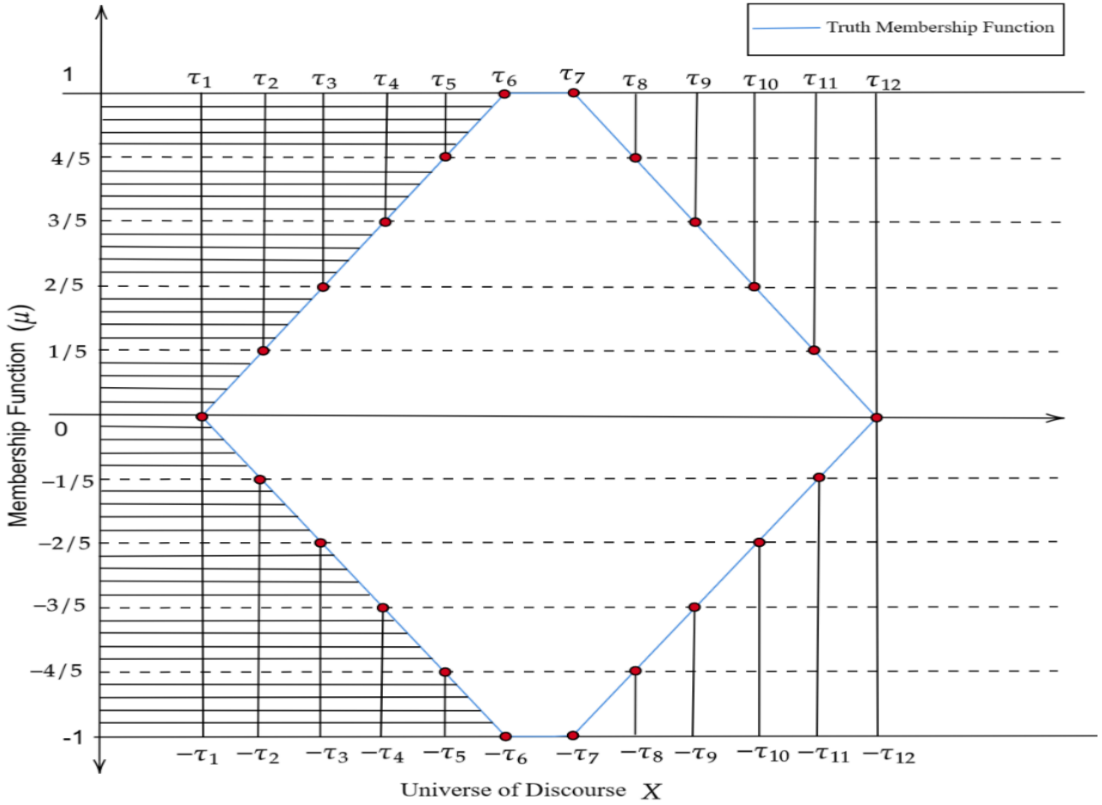

Figure 3. De-bipolarization of truth membership function left side

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The De-Bipolarization of Dodecagonal Neutrosophic number for truth membership function

$$= \frac{\tau_2-\tau_1}{2}\left(\frac{1}{5}\right) + \frac{\tau_3-\tau_2}{2}\left(\frac{2}{5}\right) + \frac{\tau_4-\tau_3}{2}\left(\frac{3}{5}\right) + \frac{\tau_5-\tau_4}{2}\left(\frac{4}{5}\right) + \frac{\tau_6-\tau_5}{2}(1) + \frac{t_7-t_6}{2}(1)$$

$$= \frac{(\tau_2 - \tau_1 + 2\tau_3 - 2\tau_2 + 3\tau_4 - 3\tau_3 + 4\tau_5 - 4\tau_4)}{10} + \frac{(\tau_7 - \tau_5)}{2}$$

$$= \frac{(-\tau_1 - \tau_2 - \tau_3 - \tau_4 + 4\tau_5)}{10} + \frac{(\tau_7 - \tau_5)}{2}$$

$$= -\frac{(\tau_1 + \tau_2 + \tau_3 + \tau_4 + \tau_5 - 5\tau_7)}{10}$$

---------- (1)

$$= \frac{\tau_7 - \tau_6}{2}(1) + \frac{\tau_8 - \tau_7}{2}\left(\frac{4}{5}\right) + \frac{\tau_9 - \tau_8}{2}\left(\frac{3}{5}\right) + \frac{\tau_{10} - \tau_9}{2}\left(\frac{2}{5}\right) + \frac{\tau_{11} - \tau_{10}}{2}\left(\frac{1}{5}\right) + \frac{\tau_{12} - \tau_{11}}{2}(0)$$

$$= \frac{(4\tau_8 - 4\tau_7 + 3\tau_9 - 3\tau_8 + 2\tau_{10} - 2\tau_9) + (\tau_{11} - \tau_{10})}{10} + \frac{(\tau_7 - \tau_6)}{2}$$

$$= \frac{(-5\tau_6 + \tau_7 + \tau_8 + \tau_9 + \tau_{10} + \tau_{11})}{10}$$

----------(2)

Adding (1) and (2) we get

$$= \frac{-(t_1 + t_2 + t_3 + t_4 + t_5) - 5t_6 + 6t_7 + t_8 + t_9 + t_{10} + t_{11}}{10}$$

Similarly for the truth negative membership function

$$= \frac{(t_1 + t_2 + t_3 + t_4 + t_5) + 5t_6 - 6t_7 - t_8 - t_9 - t_{10} - t_{11}}{10}$$

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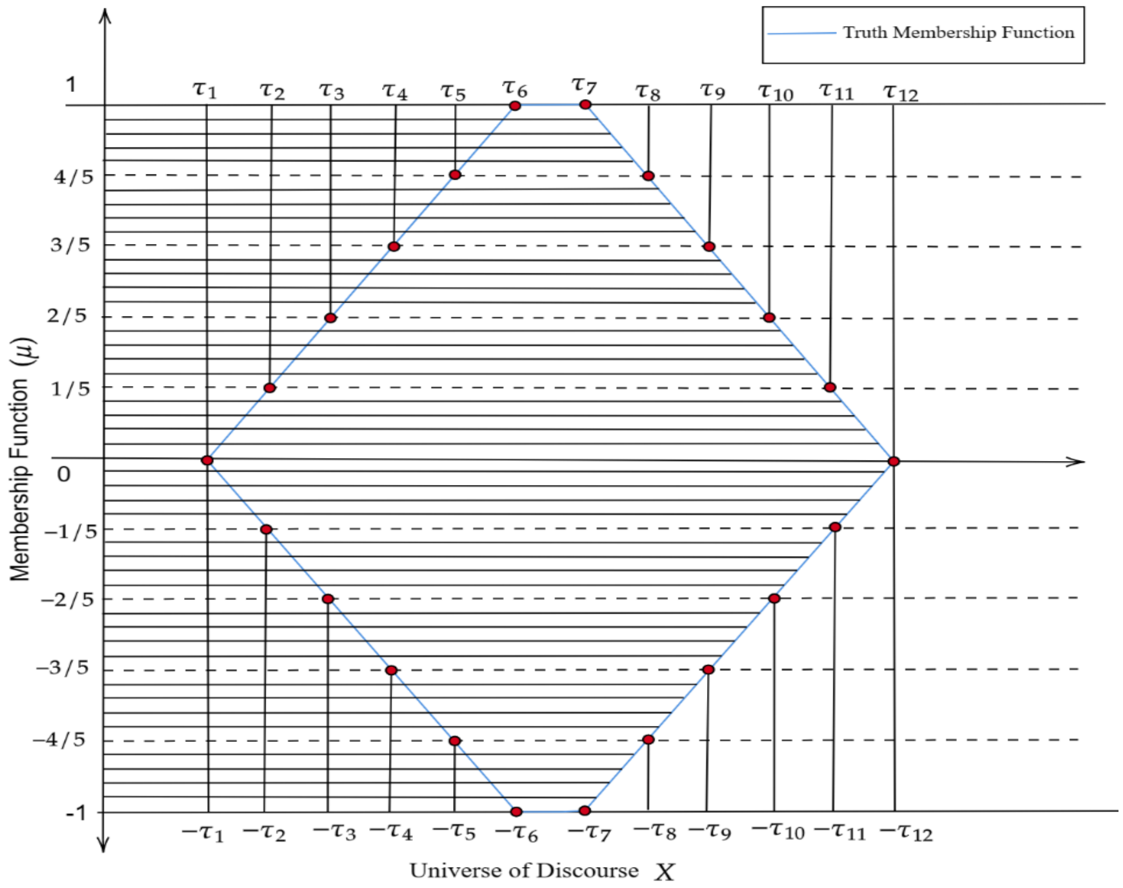

Figure 4. De-bipolarization of truth membership function right side

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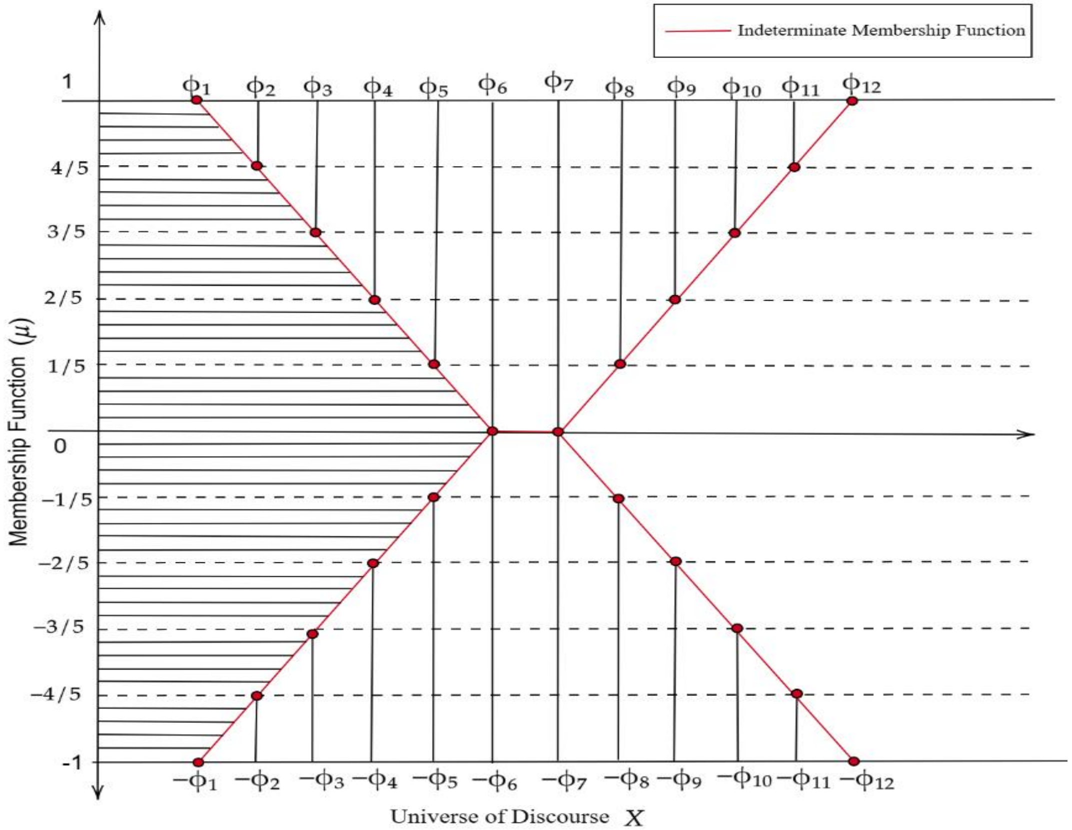

Figure 5. De-bipolarization of Indeterminacy membership function left side

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Indeterminate membership function

$$= \left(\frac{\phi_2 - \phi_1}{2}\right)(1) + \left(\frac{\phi_3 - \phi_2}{2}\right)\left(\frac{4}{5}\right) + \left(\frac{\phi_4 - \phi_3}{2}\right)\left(\frac{3}{5}\right) + \left(\frac{\phi_5 - \phi_4}{2}\right)\left(\frac{2}{5}\right) + \left(\frac{\phi_6 - \phi_5}{2}\right)\left(\frac{1}{5}\right) + \left(\frac{\phi_7 - \phi_6}{2}\right)(0)$$

$$= \left(\frac{\phi_2 - \phi_1}{2}\right) + \frac{-4\phi_2 + 4\phi_3 - 3\phi_3 + 3\phi_4 - 2\phi_4 + 2\phi_5 - \phi_5 + \phi_6}{10}$$

$$= \left(\frac{\phi_2 - \phi_1}{2}\right) + \frac{-4\phi_2 + \phi_3 + \phi_4 + \phi_5 + \phi_6}{10}$$

$$= \frac{5\phi_2 - 5\phi_1 - 4\phi_2 + \phi_3 + \phi_4 + \phi_5 + \phi_6}{10}$$

$$= \frac{-5\phi_1 + \phi_2 + \phi_3 + \phi_4 + \phi_5 + \phi_6}{10}$$

----------------------- (2)

$$= \left(\frac{\phi_7 - \phi_6}{2}\right)(0) + \left(\frac{\phi_8 - \phi_7}{2}\right)\left(\frac{1}{5}\right) + \left(\frac{\phi_9 - \phi_8}{2}\right)\left(\frac{2}{5}\right) + \left(\frac{\phi_{10} - \phi_9}{2}\right)\left(\frac{3}{5}\right) + \left(\frac{\phi_{11} - \phi_{10}}{2}\right)\left(\frac{4}{5}\right) + \left(\frac{\phi_{12} - \phi_{11}}{2}\right)(1)$$

$$= \frac{-\phi_7 + \phi_8 + 2\phi_9 - 2\phi_8 + 3\phi_{10} - 3\phi_9 + 4\phi_{11} - 4\phi_{10}}{10} + \left(\frac{\phi_{12} - \phi_{11}}{2}\right)$$

$$= \frac{-\phi_7 - \phi_8 - \phi_9 - \phi_{10} - \phi_{11} + 5\phi_{12}}{10}$$

------------------------------------(3)

Adding both the equations we get

$$= \frac{-5\phi_1 + \phi_2 + \phi_3 + \phi_4 + \phi_5 + \phi_6 - \phi_7 - \phi_8 - \phi_9 - \phi_{10} - \phi_{11} + 5\phi_{12}}{10} \quad (1)$$

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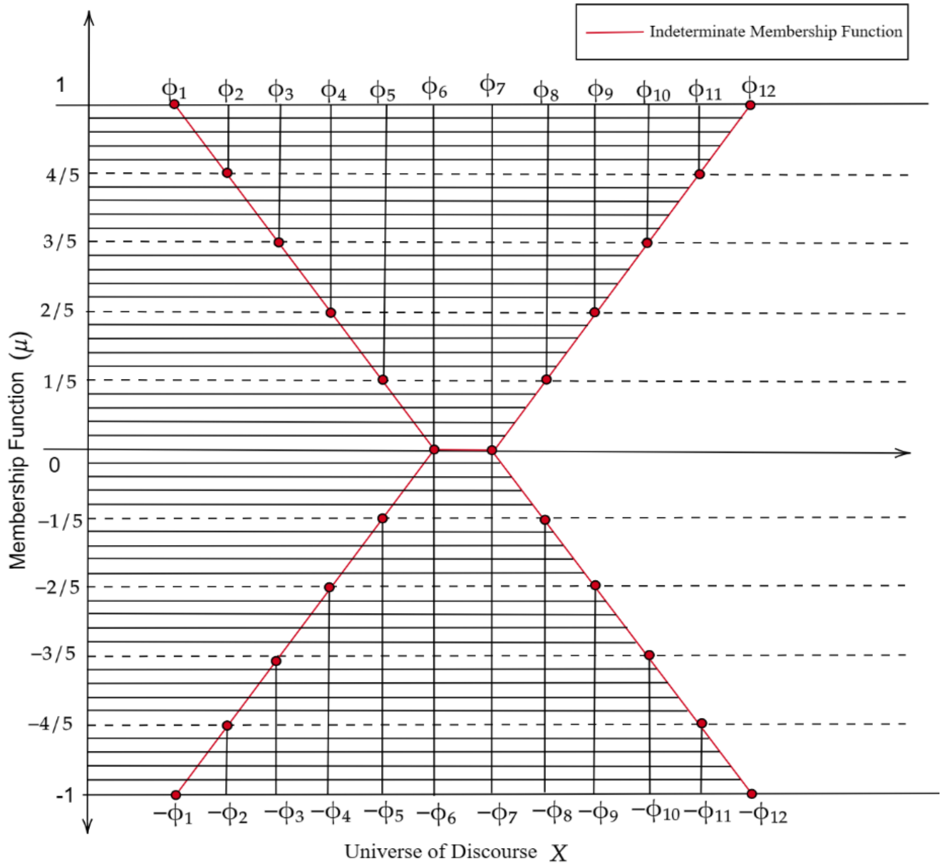

Figure 6. De-bipolarization of Indeterminacy membership function right side

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Similarly for the indeterminacy membership function negative side

$$= \frac{5\phi_1 - \phi_2 - \phi_3 - \phi_4 - \phi_5 - \phi_6 + \phi_7 + \phi_8 + \phi_9 + \phi_{10} + \phi_{11} - 5\phi_{12}}{10} \quad (10)$$

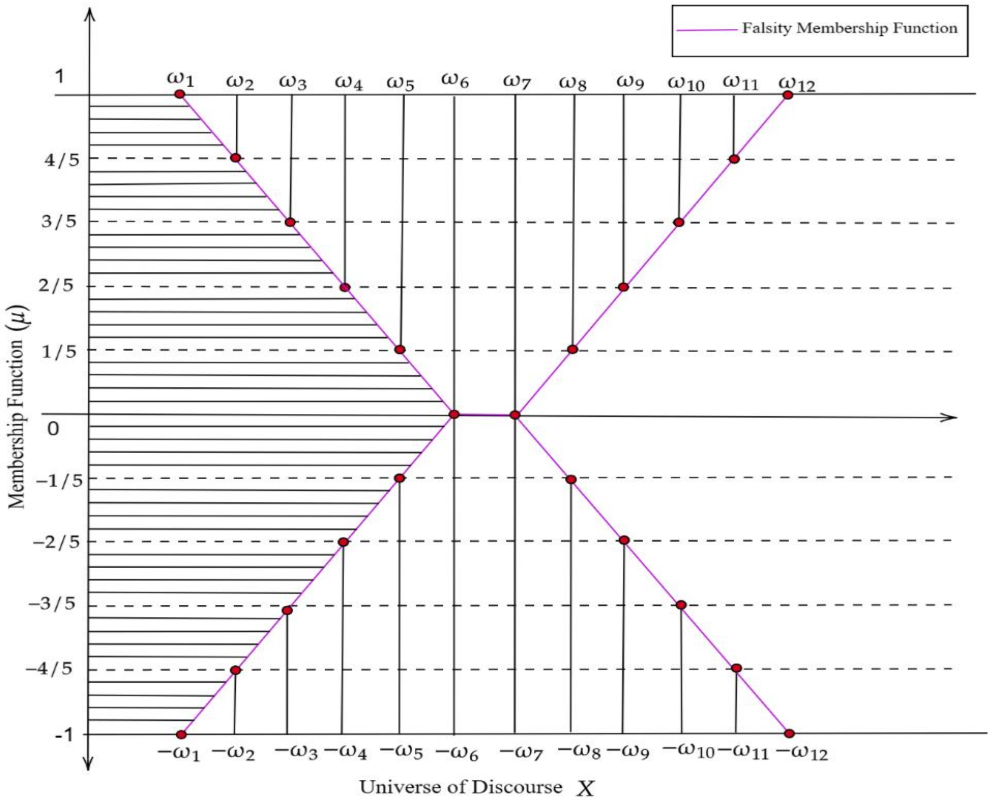

Figure 7. De-bipolarization of Falsity membership function left side

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Falsity membership function (Positive side)

$$= \left(\frac{\omega_2 - \omega_1}{2}\right)(1) + \left(\frac{\omega_3 - \omega_2}{2}\right)\left(\frac{4}{5}\right) + \left(\frac{\omega_4 - \omega_3}{2}\right)\left(\frac{3}{5}\right) + \left(\frac{\omega_5 - \omega_4}{2}\right)\left(\frac{2}{5}\right) + \left(\frac{\omega_6 - \omega_5}{2}\right)\left(\frac{1}{5}\right) + \left(\frac{\omega_7 - \omega_6}{2}\right)(0)$$

$$= \left(\frac{\omega_2 - \omega_1}{2}\right) + \frac{-4\omega_2 + 4\omega_3 - 3\omega_3 + 3\omega_4 - 2\omega_4 + 2\omega_5 - \omega_5 + \omega_6}{10}$$

$$= \left(\frac{\omega_2 - \omega_1}{2}\right) + \frac{-4\omega_2 + \omega_3 + \omega_4 + \omega_5 + \omega_6}{10}$$

$$= \frac{5\omega_2 - 5\omega_1 - 4\omega_2 + \omega_3 + \omega_4 + \omega_5 + \omega_6}{10}$$

$$= \frac{-5\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 + \omega_6}{10}$$

(11)

$$= \left(\frac{\omega_7 - \omega_6}{2}\right)(0) + \left(\frac{\omega_8 - \omega_7}{2}\right)\left(\frac{1}{5}\right) + \left(\frac{\omega_9 - \omega_8}{2}\right)\left(\frac{2}{5}\right) + \left(\frac{\omega_{10} - \omega_9}{2}\right)\left(\frac{3}{5}\right) + \left(\frac{\omega_{11} - \omega_{10}}{2}\right)\left(\frac{4}{5}\right) + \left(\frac{\omega_{12} - \omega_{11}}{2}\right)(1)$$

$$= \frac{-\omega_7 + \omega_8 + 2\omega_9 - 2\omega_8 + 3\omega_{10} - 3\omega_9 + 4\omega_{11} - 4\omega_{10}}{10} + \left(\frac{\omega_{12} - \omega_{11}}{2}\right)$$

$$= \frac{-\omega_7 - \omega_8 - \omega_9 - \omega_{10} - \omega_{11} + 5\omega_{12}}{10}$$

(12)

Adding both the equations we get

$$= \frac{-5\omega_1 + \omega_2 + \omega_3 + \omega_4 + \omega_5 + \omega_6 - \omega_7 - \omega_8 - \omega_9 - \omega_{10} - \omega_{11} + 5\omega_{12}}{10} \quad (13)$$

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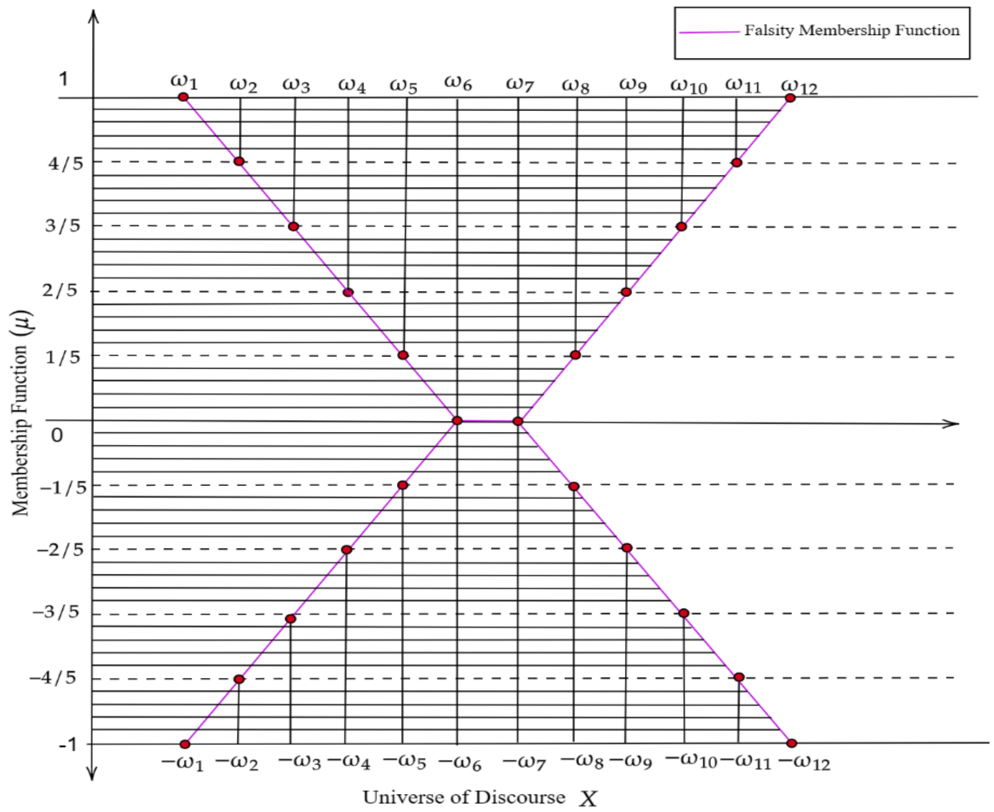

Figure 8. De-bipolarization of falsity membership function right side

Similarly for falsity membership function negative part is given as

$$= \frac{5\omega_1 - \omega_2 - \omega_3 - \omega_4 - \omega_5 - \omega_6 + \omega_7 + \omega_8 + \omega_9 + \omega_{10} + \omega_{11} - 5\omega_{12}}{10} \quad (14)$$

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Transform the single-valued Neutrosophic Number into a Crisp Number with the help of the Score Function Value.

$$\tilde{S} = \frac{2 + T - I - F}{3}$$

5. Bipolar Neutrosophic TOPSIS Method

Techniques for solving the TOPSIS method for handling a choice-making with multiple criteria problem.

Step 1: By applying the linguistic parameter in table [1], create a DM and QoS weight vector established on the choice producer's assessment of a problem involving alternates and parameters.
Step 2: create a single-valued Bipolar Heptagonal Neutrosophic number by converting the DM and Weighted vector.
Step 3: De-Bipolarization formula from equation (8*) can be utilized to transform a single-valued Neutrosophic Number by converting the single-valued Bipolar Heptagonal Neutrosophic Number.
Step 4: Locate the balanced Neutrosophic Selection Matrix.
Step 5: It is necessary to compute the Neutrosophic Positive ideally suited Solution and Neutrosophic Negative Ideally suited answer.
Step 6: Determine the distance between NPIS and NNIS and the cloud service provider.
Step 7: Assign each CSP a closeness index, then arrange the results in descending sequence.

Algorithm: Modified TOPSIS pseudocode representation for cloud selection according to the calibre of the service.

Input: Number of cloud service suppliers (n) and number of qualities of service (QoS) settings (m) entered.

Output: List of cloud service providers.

1. Enter the choice matrix and each QoS's the linguistic term's weight.
2. Create a single-valued linear Bipolar Heptagonal Neutrosophic decision matrix and corresponding weight vector S for every QoS by converting both the decision matrix and weight.
3. Create a single-valued Neutrosophic number from a bipolar one by applying the De-Bipolarization Technique.
4. **for** each $< T(P_{ij}), I(P_{ij}), F(P_{ij}) >$ in DM do

$T_{ij}^{S} = T(P_{ij}) * T(S_j)$

$I_{ij}^{S} = I(P_{ij}) + I(S_j) - I(P_{ij}) * I(S_j)$

$F_{ij}^{S} = F(P_{ij}) + F(S_j) - F(P_{ij}) * F(S_j)$

end

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5. **Compute**

$P^{+} = [\{< 1.0,0.0,0.0 > for\ each\ k \in K_1\}, \{< 0.0,1.0,1.0 > for\ each\ k \in K_2\}]$ K_1 Profit QoS

$P^{-} = [\{< 0.0,1.0,1.0 > for\ each\ k \in K_1\}, \{< 1.0,0.0,0.0 > for\ each\ k \in K_2\}]$ K_2 Charge QoS

6. **for** i = 1: n do

$$Q^{+} = Q(P_i, P^{+})$$
$$Q^{-} = Q(P_i, P^{-})$$

end

7. **for** i = 1: n do

$$CI_i = \frac{Q_i^{-}}{Q_i^{-} + Q_i^{+}}$$

end

8. The providers of cloud computing services should be arranged in decreasing order by CI_i

1. **Analysis of a case involving the QoS-based choosing of cloud service providers**

Infrastructure as a service (IaaS), Platform as a service (PaaS), and Software as a service (SaaS) are among the services offered by cloud service providers (CSPs), which also create private and public clouds

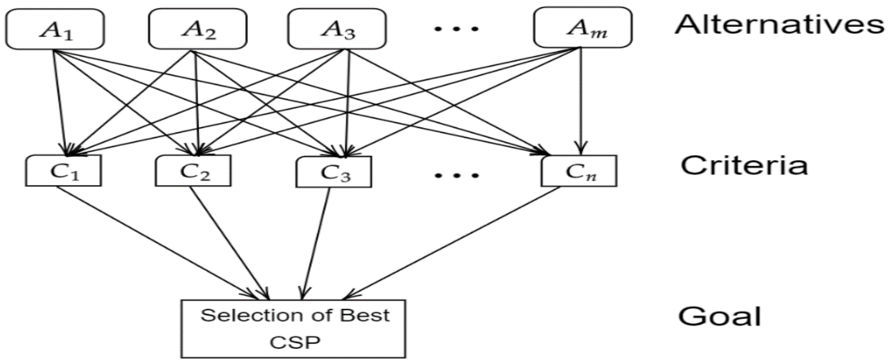

Figure 9. Three-Level Hierarchy Framework

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Table 1: Options for choosing the top cloud computing service supplier

S. No	Alternatives
1	Amazon EC2
2	Digital Ocean
3	Google
4	Microsoft Azure
5	Rackspace
6	SoftLayer

Table 2: Standards for choosing a cloud service

S. No	Criteria	
	Cost Criteria	**Benefit Criteria**
1	Cost	CPU Integer Performance
2	Network Latency	CPU Floating Point Performance
3	Sequential Disk R/W Performance Consistency	Memory Performance on Scale
4	Random Disk R/W Performance Consistency	Memory Performance on Triad
5	-	Sequential R/W Disk Performance
6	-	Random R/W Disk Performance

Table 3: Linguistic variable for decision making with SVLBHNN

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Linguistic variable	Single Valued Linear Bipolar Heptagonal Neutrosophic Number (SVLBHNN),
Extremely good	$< \begin{pmatrix} 0.88, 0.89, 0.90, 0.91, 0.92, 0.93, 0.94, 0.95, 0.96, 0.97, 0.98, 0.99; \\ 0.43, 0.44, 0.45, 0.46, 0.47, 0.48, 0.49, 0.50, 0.51, 0.52, 0.53, 0.54; \\ 0.323, 0.324, 0.325, 0.326, 0.327, 0.0.328, 0.329, 0.330, 0.331, 0.332, 0.333, 0.334 \end{pmatrix} \begin{pmatrix} -0.52, -0.53, -0.54, -0.55, -0.56, -0.57, -0.58, -0.59, -0.60, -0.61, -0.62, -0.63; \\ -0.26, -0.27, -0.28, -0.29, -0.30, -0.31, -0.32, -0.33, -0.34, -0.35, -0.36, -0.37 \\ -0.18, -0.19, -0.20, -0.21, -0.22, -0.23, -0.24, -0.25, -0.26, -0.27, -0.28, -0.29 \end{pmatrix} >$
Very Good	$< \begin{pmatrix} 0.77, 0.78, 0.79, 0.80, 0.81, 0.82, 0.83, 0.84, 0.85, 0.86, 0.87, 0.88; \\ 0.38, 0.39, 0.40, 0.41, 0.42, 0.43, 0.44, 0.45, 0.46, 0.47, 0.48, 0.49; \\ 0.28, 0.29, 0.30, 0.31, 0.32, 0.33, 0.34, 0.35, 0.36, 0.37, 0.38, 0.39 \end{pmatrix} \begin{pmatrix} -0.55, -0.56, -0.57, -0.58, -0.59, -0.60, -0.61, -0.62, -0.63, -0.64, -0.65, -0.66; \\ -0.32, -0.33, -0.34, -0.35, -0.36, -0.37, -0.38, -0.39, -0.40, -0.41, -0.42, -0.43; \\ -0.20, -0.21, -0.22, -0.23, -0.24, -0.25, -0.26, -0.27, -0.28, -0.29, -0.30, -0.31 \end{pmatrix} >$
Good	$< \begin{pmatrix} 0.71, 0.72, 0.73, 0.74, 0.75, 0.76, 0.77, 0.78, 0.79, 0.80, 0.81, 0.82; \\ 0.33, 0.34, 0.35, 0.36, 0.37, 0.38, 0.39, 0.40, 0.41, 0.42, 0.43, 0.44, \\ 0.26, 0.27, 0.28, 0.29, 0.30, 0.33, 0.34, 0.35, 0.36, 0.37, 0.38, 0.39 \end{pmatrix} \begin{pmatrix} -0.47, -0.48, -0.49, -0.50, -0.51, -0.52, -0.53, -0.54, -0.55, -0.56, -0.57, -0.58; \\ -0.38, -0.39, -0.40, -0.41, -0.42, -0.43, -0.44, -0.45, -0.46, -0.47, -0.48, -0.49; \\ -0.24, -0.25, -0.26, -0.27, -0.28, -0.29, -0.30, -0.31, -0.32, -0.33, -0.34, -0.35 \end{pmatrix} >$
Medium Good	$< \begin{pmatrix} 0.66, 0.67, 0.68, 0.69, 0.70, 0.71, 0.72, 0.73, 0.74, 0.75, 0.76, 0.77; \\ 0.37, 0.38, 0.39, 0.40, 0.41, 0.42, 0.43, 0.44, 0.45, 0.46, 0.47, 0.48; \\ 0.32, 0.33, 0.34, 0.35, 0.36, 0.37, 0.38, 0.39, 0.40, 0.41, 0.42, 0.43 \end{pmatrix} \begin{pmatrix} -0.42, -0.43, -0.44, -0.45, -0.46, -0.47, -0.48, -0.49, -0.50, -0.51, -0.52, -0.53; \\ -0.43, -0.44, -0.45, -0.46, -0.47, -0.48, -0.49, -0.50, -0.51, -0.52, -0.53, -0.54; \\ -0.27, -0.28, -0.29, -0.30, -0.31, -0.32, -0.33, -0.34, -0.35, -0.36, -0.37, -0.38) \end{pmatrix} >$
Medium	$< \begin{pmatrix} 0.36, 0.37, 0.38, 0.39, 0.40, 0.41, 0.42, 0.43, 0.44, 0.45, 0.46, 0.47; \\ 0.36, 0.37, 0.38, 0.39, 0.40, 0.41, 0.42, 0.43, 0.44, 0.45, 0.46, 0.47; \\ 0.40, 0.41, 0.42, 0.43, 0.44, 0.45, 0.46, 0.47, 0.48, 0.49, 0.50, 0.51 \end{pmatrix} \begin{pmatrix} -0.36, -0.37, -0.38, -0.39, -0.40, -0.41, -0.42, -0.43, -0.44, -0.45, -0.46, -0.47; \\ -0.36, -0.37, -0.38, -0.39, -0.40, -0.41, -0.42 - 0.43, -0.44, -0.45, -0.46, -0.47; \\ -0.40, -0.41, -0.42, -0.43, -0.44, -0.45, -0.46, -0.47, -0.48, -0.49, -0.50, -0.51 \end{pmatrix} >$
Medium Bad	$< \begin{pmatrix} 0.29, 0.30, 0.31, 0.32, 0.33, 0.34, 0.35, 0.36, 0.37, 0.38, 0.39, 0.40; \\ 0.40, 0.41, 0.42, 0.43, 0.44, 0.45, 0.46, 0.47, 0.48, 0.49, 0.50, 0.51; \\ 0.47, 0.48, 0.49, 0.50, 0.51, 0.52, 0.53, 0.54, 0.55, 0.56, 0.57, 0.58 \end{pmatrix}$

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	$\begin{pmatrix} -0.31, -0.32, -0.33, -0.34, -0.35, -0.36, -0.37, -0.38, -0.39, -0.40, -0.41, -0.42; \\ -0.45, -0.46, -0.47, -0.48, -0.49, -0.50, -0.51, -0.52, -0.53, -0.54, -0.55, -0.56; \\ -0.50, -0.51, -0.52, -0.53, -0.54, -0.55, -0.56, -0.57, -0.58, -0.59, -0.60, -0.61 \end{pmatrix} >$
Bad	$< \begin{pmatrix} 0.20, 0.21, 0.22, 0.23, 0.24, 0.25, 0.26, 0.27, 0.28, 0.29, 0.30, 0.31; \\ 0.51, 0.52, 0.53, 0.54, 0.55, 0.56, 0.57, 0.58, 0.59, 0.60, 0.61, 0.62; \\ 0.62, 0.63, 0.64, 0.65, 0.66, 0.67, 0.68, 0.69, 0.70, 0.71, 0.72, 0.73; \end{pmatrix} \begin{pmatrix} -0.28, -0.29, -0.30, -0.31, -0.32, -0.33, -0.34, -0.35, -0.36, -0.37, -0.38, -0.39; \\ -0.50, -0.51, -0.52, -0.53, -0.54, -0.55, -0.56, -0.57, -0.58, -0.59, -0.60, -0.61 \\ -0.55, -0.56, -0.57, -0.58, -0.59, -0.60, -0.61, -0.62, -0.63, -0.64, -0.65, -0.66 \end{pmatrix} >$
Very Bad	$< \begin{pmatrix} 0.11, 0.12, 0.13, 0.14, 0.15, 0.16, 0.17, 0.18, 0.19, 0.20, 0.21, 0.22; \\ 0.58, 0.59, 0.60, 0.61, 0.62, 0.63, 0.64, 0.65, 0.66, 0.67, 0.68, 0.69; \\ 0.67, 0.68, 0.69, 0.70, 0.71, 0.72, 0.73, 0.74, 0.75, 0.76, 0.77, 0.78 \end{pmatrix} \begin{pmatrix} -0.14, -0.15, -0.16, -0.17, -0.18, -0.19, -0.20, -0.21, -0.22, -0.23, -0.24, -0.25; \\ -0.56, -0.57, -0.58, -0.59, -0.60, -0.61, -0.62, -0.63, -0.64, -0.65, -0.66, -0.67; \\ -0.66, -0.67, -0.68, -0.69, -0.70, -0.71, -0.72, -0.73, -0.74, -0.75, -0.76, -0.77 \end{pmatrix} >$
Very Very Bad	$< \begin{pmatrix} 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10, 0.11, 0.12, 0.13, 0.14; \\ 0.63, 0.64, 0.65, 0.66, 0.67, 0.68, 0.69, 0.70, 0.71, 0.72, 0.73, 0.74; \\ 0.74, 0.75, 0.76, 0.77, 0.78, 0.79, 0.80, 0.81, 0.82, 0.83, 0.84, 0.85, \end{pmatrix} \begin{pmatrix} -0.65, -0.66, -0.67, -0.68, -0.69, -0.70, -0.71, -0.72, -0.73, -0.74, -0.75, -0.76; \\ -0.18, -0.19, -0.20, -0.21, -0.22, -0.23, -0.24, -0.25, -0.26, -0.27, -0.28, -0.29; \\ -0.75, -0.76, -0.77, -0.78, -0.79, -0.80, -0.81, -0.82, -0.83, -0.84, -0.85, -0.86 \end{pmatrix} >$

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Table 4: Bipolar to SVNN Conversion

Linguistic variable	Single Valued Linear Neutrosophic Number (SVLBHNN)
Extremely Good (EG)	$<(0.936,0.510,0.3186)>$
Very Good (VG)	$<(0.8880,0.516,0.384)>$
Good (G)	$<(0.804,0.576,0.408)>$
Medium Good (MG)	$<(0.744,0.5580,0.450)>$
Medium (M)	$<(0.5280,0.5520,0.5760)>$
Medium Bad (MB)	$<(0.4560,0.6060,0.6780)>$
Bad (B)	$<(0.3840,0.7020,0.7980)>$
Very Bad (VB)	$<(0.246,0.780,0.8940)>$
Very Very Bad (VVB)	$<(0.1920,0.8640,0.9900)>$

Table 5: Linguistic Variable for the Criteria

CSP	C	NL	SDRWPL	RDRWPC	CPUIP	CPUFPP	MPS	MPT	SRWDP	RRWDP
Amazon EC2	B	VB	VB	B	B	B	G	G	B	B
Digital Ocean	B	M	VB	VB	B	B	G	G	B	B
Google	B	G	B	B	B	B	G	G	VB	VB
Microsoft Azure	B	M	B	B	VB	VB	M	M	B	B
Rackspace	M	M	M	M	B	B	G	G	G	B
SoftLayer	B	VB	B	M	B	B	G	G	M	M

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Table 6: Vector Weight for the Criteria: Linguistic Variables

QoS	C	NL	SDRWPL	RDRWPC	CPUIP	CPUFPP	MPS	MPT	SRWDP	RRWDP
Weight	G	M	VB	B	VG	G	B	M	VB	B

Table 7: Matrix of decisions for choosing the options

CSP	C	NL	SDRWPL	RDRWPC	CPUIP
Amazon EC2	< (0.3840,0.7020,0.7980 >	< (0.246,0.780,0.8940) >	< (0.246,0.780,0.8940) >	< (0.3840,0.7020,0.7980 >	< (0.3840,0.7020,0.7980 >
Digital Ocean	< (0.3840,0.7020,0.7980 >	< (0.5280,0.5520,0.576 >	< (0.246,0.780,0.8940) >	< (0.246,0.780,0.8940) >	< (0.3840,0.7020,0.7980 >
Google	< (0.3840,0.7020,0.7980 >	< (0.804,0.576,0.408) >	< (0.3840,0.7020,0.7980) >	< (0.3840,0.7020,0.7980 >	< (0.3840,0.7020,0.7980 >
Microsoft Azure	< (0.3840,0.7020,0.7980 >	< (0.5280,0.5520,0.576 >	< (0.3840,0.7020,0.7980) >	< (0.3840,0.7020,0.7980 >	< (0.246,0.780,0.8940) >
Rackspace	< (0.5280,0.5520,0.5760 >	< (0.5280,0.5520,0.576 >	< (0.5280,0.5520,0.5760) >	< (0.5280,0.5520,0.5760 >	< (0.3840,0.7020,0.7980 >
SoftLayer	< (0.3840,0.7020,0.7980 >	< (0.246,0.780,0.8940) >	< (0.3840,0.7020,0.7980) >	< (0.5280,0.5520,0.5760 >	< (0.3840,0.7020,0.7980 >

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Table 8: Using the selection makers' opinions as a guide, the decision matrix

QoS	C	NL	SDRWPL	RDRWPC	CPUIP	CPUFPP	MPS	MPT	SRWDP	RRWDP
Weight	< (0.804, 0.576, 0.408) >	< (0.5280, 0.5520, 0.5760) >	< (0.246, 0.780, 0.8940) >	< (0.3840, 0.7020, 0.7980) >	< (0.8880, 0.516, 0.384) >	< (0.804, 0.576, 0.408) >	< (0.3840, 0.7020, 0.7980) >	< (0.5280, 0.5520, 0.5760) >	< (0.246, 0.780, 0.8940) >	< (0.3840, 0.7020, 0.7980) >

Table 9: Weighted vector and criterion decision matrix

CSP	C	NL	SDRWPL	RDRWPC	CPUIP
Amazon EC2	< (0.3087,0.8736,0.8804) >	< (0.1298,0.9014,0.955 >	< (0.06051,0.9516,0.9887 >	< (0.1474,0.9112,0.9592) >	< (0.3409,0.8557,0.8755 >
Digital Ocean	< (0.3087,0.8736,0.8804) >	< (0.2787,0.7993,0.820 >	< (0.06051,0.9516,0.9887 >	< (0.0945,0.9344,0.9785) >	< (0.3409,0.8557,0.8755 >
Google	< (0.3087,0.8736,0.8804) >	< (0.4245,0.8100,0.748 >	< (0.09446,0.9344,0.9785 >	< (0.1474,0.9112,0.9592) >	< (0.3409,0.8557,0.8755 >
Microsoft Azure	< (0.3087,0.8736,0.8804) >	< (0.2787,0.7993,0.820 >	< (0.09446,0.9344,0.9785 >	< (0.1474,0.9112,0.9592) >	< (0.2184,0.8935,0.9347 >

CSP	CPUFPP	MPS	MPT	SRWDP	RRWDP
Amazon EC2	< (0.3087,0.8736,0.8804) >	< (0.1474,0.9112,0.9592) >	< (0.4245,0.8100,0.7489) >	< (0.0944,0.9344,0.9785) >	< (0.1474,0.9112,0.9592) >
Digital Ocean	< (0.3087,0.8736,0.8804) >	< (0.1474,0.9112,0.9592) >	< (0.4245,0.8100,0.7489) >	< (0.0944,0.9344,0.9785) >	< (0.1474,0.9112,0.9592) >
Google	< (0.3087,0.8736,0.8804) >	< (0.14741,0.9112,0.9592) >	< (0.4245,0.8100,0.7489) >	< (0.0605,0.9516,0.9887) >	< (0.0945,0.9344,0.9785) >
Microsoft Azure	< (0.1978,0.9067,0.9372) >	< (0.09446,0.9344,0.9785) >	< (0.2787,0.7993,0.8202) >	< (0.0944,0.9344,0.9785) >	< (0.1474,0.9112,0.9592) >
Rackspace	< (0.3087,0.8736,0.8804) >	< (0.1474,0.9112,0.9592) >	< (0.4245,0.8100,0.7489) >	< (0.1977,0.9067,0.9372) >	< (0.1474,0.9112,0.9592) >
SoftLayer	< (0.3087,0.8736,0.8804) >	< (0.1474,0.9112,0.9592) >	< (0.4245,0.8100,0.7489) >	< (0.1298,0.9014,0.9550) >	< (0.2027,0.8665,0.9143) >

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Table 10: Neutrosophic decision matrix evaluation of SVNPIS and SVNNIS

	C	NL	SDRWPL	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)
SVNPIS	(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 11: The ranking of each cloud service provider and their distance from SVNPIS and SVNNIS

CSP	D_i^+	D_i^-	CL	Ranking
Amazon EC2 (AZ)	5.55927	4.41989	0.44291	3
Digital Ocean (DO)	5.54477	4.4543	0.44547	2
Google (G)	5.7364	4.2627	0.42630	5
Microsoft Azure (MZ)	5.86785	4.13133	0.41316	6
RackSpace (RS)	5.72375	4.2754	0.4279	4
SoftLayer (SL)	5.4395	4.560	0.4560	1

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Table 12: CSPs compared to SVNN and SVLBDoNN

S. No	CSP	SVNN	SVLBHNN
1	Amazon EC2	0.4732	0.456
2	Digital Ocean	0.4558	0.4279
3	Google	0.4338	0.41316
4	Microsoft Azure	0.4133	0.4263
5	Rack Space	0.4251	0.44547
6	SoftLayer	0.4765	0.44291

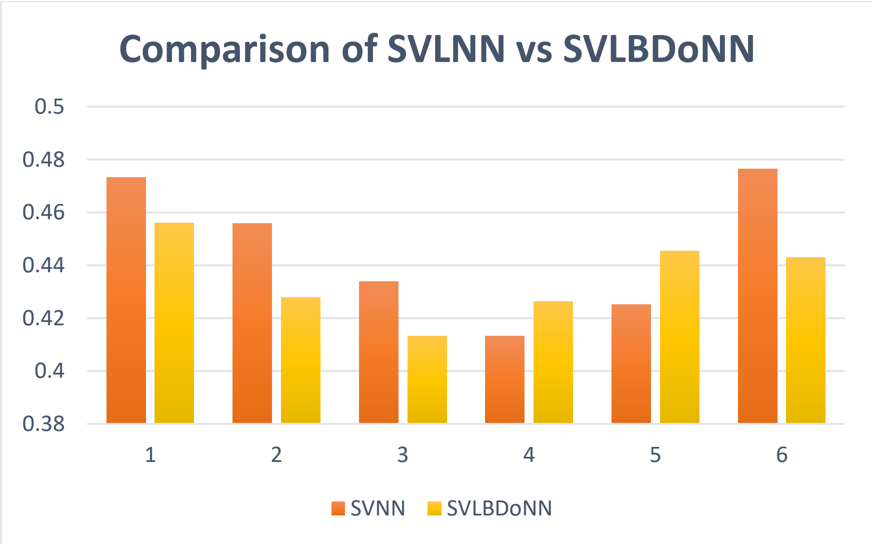

Figure 12. CSPs compared to SVNN and SVLBDoNN

Table 13: Comparison of the suggested approach with other approaches found in the literature

MCDM methods	**Rank**
Proposed method	SoftLayer > Digital Ocean > Amazon EC2 > Rackspace > Google > Microsoft Azure
N-TOPSIS METHOD [11]	SoftLayer > Amazon EC2 > Digital Ocean > Google > Rackspace > Microsoft Azure
Neutrosophic VIKOR METHOD [13]	Amazon EC2 > SoftLayer > Digital Ocean > Google > Rackspace > Microsoft Azure
Neutrosophic TOPSIS [14]	SoftLayer > Amazon EC2 > Digital Ocean > Google > Rackspace > Microsoft Azure
FUZZY TOPSIS [10]	SoftLayer > Amazon EC2 > Digital Ocean > Google > Rackspace > Microsoft Azure
AHP [15]	Amazon EC2 > SoftLayer > Rackspace > Google > Microsoft Azure > Digital Ocean
Improved TOPSIS [12]	SoftLayer > Amazon EC2 > Digital Ocean > Rackspace > Microsoft Azure > Google >

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6. Conclusion

In the modern era, cloud computing has upended the company's business plan. The rising quantity of cloud services providing organizations and the high demand from customers have made it difficult to choose the top support supplier for the job at hand. In the modern era, cloud computing has upended the business model. As a means of handling vague decisions, a single valued linear bipolar Dodecagonal Neutrosophic number is provided. The removal area technique is used to achieve its De-Bipolarization. An example of selecting a service provider for cloud computing according to the improved level of providers. The best suppliers of cloud-based offerings are analyzed and ranked using the TOPSIS methodology. A Neutrosophic number with a single value is used to compare the outcomes with other methods found in the literature. To improve efficiency later on, the work could be expanded to include bipolar uncertain cliques, or it could be combined with the notion of rough cliques to address uncertainty.

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