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NEUTROSOPHIC MAGDM BASED ON CRITIC-EDAS STRATEGY USING GEOMETRIC AGGREGATION OPERATOR

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Abstract: Nowadays career choosing is a very difficult job for many students. This paper primarily addresses the concerns of those students who face difficulty in choosing the right career option for themselves, using multi-attribute group decision-making (MAGDM) methodologies based on CRITIC (Criteria Importance Through Inter criteria Correlation) and EDAS (Evaluation based on Distance from Average Solution) strategies under the single-valued neutrosophic set (SVNS) environment. First, the CRITIC strategy is used to calculate the weights of the attributes and then these weights are used to develop EDAS strategy in the SVNS environment. Since the usage of the geometric operator CRITIC-EDAS has not before been documented in the literature, this study is distinctive. A realistic example of commerce students' career selection problem is discussed.

Keywords: MAGDM, SVNSs, CRITIC strategy, EDAS strategy.

MSC: 90Bxx, 90B50, 91B06.

1. INTRODUCTION

Career selection is a big issue for students because of the changing character of the world economy. Young students today are more and more concerned about picking the right career path. Students must take into account a variety of considerations when selecting a career. A student's decisions may be influenced by their parents, coaches, or any other role models in their lives. In this scenario, Multi-Attribute Group Decision-Making (MAGDM) may help them in finding the best career options. This paper demonstrates how a student can choose the right career option using MAGDM.

MAGDM is a cognitive process to select the best alternative with respect to multiple conflicting criteria. The "Criteria Importance Through Inter Criteria Correlationc (CRITIC) "[1] strategy is an objective strategy for determining criteria weights and that takes into account the strength of contrast and conflict in the Decision-Making (DM) problem's structure. It is a correlation method based on analysis of a decision matrix to determine the information included in the criteria used to evaluate the alternatives. On the other hand, "Evaluation based on Distance from Average Solution (EDAS)" [2] strategy plays a significant role in DM problem, especially when there are many conflicting criteria. The evaluation of alternatives in this strategy is based on the distance of each alternative from the average solution with respect to each attribute. These two MAGDM strategies are combined in this paper in order to assist students in making their best career choice.

Most DM problems lack accurate information about real-world issues, which complicates the DM process. Zadeh [3] founded the "Fuzzy Set (FS)" theory to deal with subjective and imprecise data. The FS has single membership function $\mu_A(x) \in [0,1]$. In some cases, the membership function cannot handle certain cases where it is hard to define $\mu_A(x)$ by one specific value. To address the lack of knowledge about non-membership degree, Atanassov [4] proposed "Intuitionistic Fuzzy Set (IFS)" , which is an extension of Zadeh's FS. Although the IFS theory has been established and generalized, it cannot deal with all uncertainties in many real-world problems. Indeterminate and inconsistent data are examples of specific sorts of uncertainty that cannot be handled. To solve this problem, Smarandache [5] defined the "Neutrosophic Set (NS)" which is characterized by three independent membership functions viz. "Truth-Membership Function (TMF)", "Indeterminacy-Membership Function (IMF)", and "Falsity-Membership Function (FMF)", and appears to be a very helpful tool for working with incomplete, indeterminate, and inconsistent data. Recently, NSs have drawn a lot of attention as a fascinating field of research. Wang et al. [6] proposed the concept of "Interval Neutrosophic Set (INS)" and "Single Valued Neutrosophic Set (SVNS)"[7], which are subclasses of the NS, as well as the set-theoretic operators and features of SVNSs and INSs. Ye [8] introduced the SVNS correlation coefficients and applied them to DM problems. Sahin [9] defined score and accuracy functions for Single Valued Neutrosophic Numbers (SVNNs). Peng et al.[10] defined the SVNS operations and developed the weighted and ordered weighted averaging and geometric aggregation operators for SVNNs.

Various DM strategies have contributed to the development of Multi Attribute DM (MADM) research in the neutrosophic field. Biswas et al. [11] developed the TOPSIS strategy in the neutrosophic field to select the most suitable tablet with respect to some attributes. Pouresmaeil et al. [12] combined the TOPSIS and VIKOR strategies in SVNSs environment. Bausys et al. [13] developed the COPRAS method for SVNSs and used it to the location selection of a liquefied natural gas facility. Zavadskas et al. [14] extended the WASPAS strategy for SVNSs. For the MADM problem, Biswas et al. [15] defined the Grey Relational Analysis (GRA) approach. Integrated neutrosophic ANP and VIKOR approaches for attaining sustainable supplier selection were developed by Abdel-Baset et al. [16].

Various criterion weighting procedures have been established in the literature [17] for the MADM process. The methodologies for calculating weights are divided into two categories: objective weight and subjective weight [18]. The CRITIC approach [1] is one of the weighting models that uses the standard deviation and correlation coefficient to measure the value of each attribute and generate the weights of attributes for the MADM technique. To solve the 3PRLPs with interval type-2 fuzzy sets, Ghorabaee et al. [19] discussed a hybrid model with the CRITIC and WASPAS strategies. Ghorabaee et al. [20] presented the combined MADM model that included the EDAS,CRITIC,and SWARA strategies. For 5G industry assessment on PFSs, Peng et al. [21] developed the CRITIC-CoCoSo strategy. Wei et al. [22] developed the hybrid model that included GRA and CRITIC techniques to assess and select the best location for EVCSs in the PULTSs environment. For financial risk assessment challenges, Peng and Huang [23] proposed a hybrid model combining CRITIC and CoCoSo strategies. To tackle the MADM procedure, Liang [24] proposed a hybrid strategy combining CRITIC and EDAS models under IFSs.

Rani et al. [25] used the SVNS-CRITIC-MULTIMOORA framework to identify multi-criteria food waste treatment strategies. Krishankumar et al. [26] used the CRITIC strategy to determine the significance of functional factors. Kar et al. [27] evaluated weights of attributes by using CRITIC in the non-linear space and they also use WASPAS procedure to rank cloud vendors. Krishankumar et al. [28] did three major works in their paper. Firstly, they introduced a novel attitudinal evidence-based Bayesian approach for criteria weight estimation. Secondly, they determined experts' weights using variance approach, and thirdly they used EDAS strategy to prioritizing zero-carbon measures. Shrivathsan et al. [29] used the entropy measures to calculate the weight and they ranked the test by using the EDAS strategy.

Tan and Zhang [30] extended the EDAS strategy in refined SVNs environment . Mallick and Pramanik [31] developed the trapezoidal neutrosophic EDAS strategy. Xu et al. [32] proposed the Single Valued (SV) complex NS EDAS and applied it to green supplier selection. Fan el al. [33] defined the SV triangular neutrosophic EDAS. Supciller and Toprak [34] developed the neutrosophic EDAS and illustrated the example of wind turbines. Han and Wei [35] extended the EDAS strategy on multivalued NS environment. Li et al. [36] developed the linguistic neutrosophic

EDAS strategy. Wang et al. [37] defined the 2-tuple linguistic NS-EDAS strategy. Karasan and Kahraman [38, 39] proposed the INS-EDAS and applied it in different problem. Peng and Dai [40] developed the INS-MADM. Stanujkic [41] devepoled the EDAS strategy for SVNS environment.

The criteria weight computation procedures are classified as objective weight and subjective weight. The CRITIC approach is one of the weighting models to estimate the objective weights of the attributes using the standard deviation and the correlation coefficient to quantify the value of each attribute and computes the attribute weights of MADM procedure.

The EDAS method can be more efficient for solving complex problems whose solution requires assessment and prediction, because truth- and falsity-membership functions can be used for expressing the level of satisfaction and dissatisfaction about an attitude. We combine the CRITIC and EDAS strategies in the neutrosophic environment to get better results.

Comparing with the VIKOR and TOPSIS, it can be said that EDAS method also evaluates the alternatives based on their separation from the ideal or preferential point. However, instead of the distance from two extreme ideal points (i.e., positive and negative), in EDAS, the distances of the alternatives from the average solution (such as PDA and NDA) are calculated. The preferred alternative is identified based on higher PDA and lower NDA values.Since the EDAS method considers the average solution point as the yardstick, it is free from extreme point variation and decision-making fluctuations. Therefore, the EDAS algorithm operates well in an uncertain environment and can deal with various complex decision-making problems by providing better accuracy and aggregation.

The research gap of this paper is stated as follows:

- In this paper, the SVNN weighted geometric aggregation operator is used, which does not appear in the literature.
- The CRITIC method acquires fairly objective weights in MAGDM situations. Based on a study of the evaluation matrix, it collects all preference data from the evaluation of the criteria. In other words, by measuring the information inherent in each evaluation criterion, the objective weights are used. Therefore, it is necessary to extend the CRITIC approach in SVNS environment to handle qualitative information.
- The EDAS method is an effective tool to proceed classification and decision for conflicting attributes. The EDAS approach is based on two important factors: PDA and NDA. In determining PDA and NDA, standard EDAS algorithms assume that all decision makers are perfectly rational. Thus, a technique must be developed that models NS information and evaluates the best alternative that helps students to select the best option for their career.

The novelty of the paper is reflected from the fact that CRITIC-EDAS strategy using geometric aggregation operator is not reported in the literature in SVNS environment.

The following is an outline of the structure of the paper. The fundamental concept of NSs is discussed in Section 2. In Section 3, we define a CRITIC strategy for SVNNs to calculate the weights of the attributes. We develop the CRITIC-EDAS Strategy using geometric operator for SVNs in Section 4 to evaluate the best alternative. The feasibility of the proposed strategies is illustrated in Section 5 with a realistic example. Finally, in Section 6, we conclude the paper by providing future research directions.

2. SOME PRELIMINARIES

Definition 2.1 [5]: An NS φ is characterised by TMF $t_\varphi(\gamma)$, IMF $i_\varphi(\gamma)$ and FMF $f_\varphi(\gamma)$. These three membership functions $t_\varphi(\gamma), i_\varphi(\gamma)$ and $f_\varphi(\gamma)$ in E are real standard and non- standard subsets of $]^{-}0, 1^{+}[$ such that $t_\varphi(\gamma), i_\varphi(\gamma), f_\varphi(\gamma) : E \to]^{-}0, 1^{+}[$. Thus, there is no restriction on the sum of $t_\varphi(\gamma), i_\varphi(\gamma)$ and $f_\varphi(\gamma)$, so that $^{-}0 \le t_\varphi(\gamma) + i_\varphi(\gamma) + f_\varphi(\gamma) \le 3^{+}$.

Definition 2.2 [7]: Assume that E be the universal set. An SVNS B is characterised by TMF $t_\varphi(\gamma)$, IMF $i_\varphi(\gamma)$ and FMF $f_\varphi(\gamma)$. A SVNS B is denoted by $B = \{\gamma : t_\varphi(\gamma), i_\varphi(\gamma), f_\varphi(\gamma)|\gamma \in E\}$ where $t_\varphi(\gamma), i_\varphi(\gamma), f_\varphi(\gamma) : E \to]0, 1[$ for each $\gamma \in E$. Then the sum of $t_\varphi(\gamma), i_\varphi(\gamma)$, and $f_\varphi(\gamma)$ satisfies the condition $0 \le t_\varphi(\gamma) + i_\varphi(\gamma) + f_\varphi(\gamma) \le 3$.

Definition 2.3 [42]: Let $\varphi_1 =< t_{\varphi_1}, i_{\varphi_1}, f_{\varphi_1} >$ and $\varphi_2 =< t_{\varphi_2}, i_{\varphi_2}, f_{\varphi_2} >$ be two SVNNs. Then the following operations hold:

(i) $\varphi_1 + \varphi_2 =< t_{\varphi_1} + t_{\varphi_2} - t_{\varphi_1}.t_{\varphi_2},\ i_{\varphi_1}.i_{\varphi_2},\ f_{\varphi_1}.f_{\varphi_2} >$

(ii) $\varphi_1.\varphi_2 =< t_{\varphi_1}.t_{\varphi_2},\ i_{\varphi_1} + i_{\varphi_2} - i_{\varphi_1}.i_{\varphi_2},\ f_{\varphi_1} + f_{\varphi_2} - f_{\varphi_1}.f_{\varphi_2} >$

$(iii)\lambda\varphi_1 =< 1 - (1 - t_{\varphi_1})^\lambda, 1 - (1 - i_{\varphi_1})^\lambda, 1 - (1 - f_{\varphi_1})^\lambda >, \quad \lambda > 0$

$(iv)\varphi_1^\lambda =< t_{\varphi_1}^\lambda, i_{\varphi_1}^\lambda, f_{\varphi_1}^\lambda >, \quad \lambda > 0$

Definition 2.4 [9]: Let $\varphi =< t_\varphi, i_\varphi, f_\varphi >$ be an SVNN. A score function (Sc) of an SVNN, based on the TMF, IMF and FMF is defined as

$$Sc(\varphi) = \frac{1 + t_\varphi - 2i_\varphi - f_\varphi}{2}, \quad -1 \le Sc(\varphi) \le 1 \tag{1}$$

Definition 2.5: Let $\varphi_k =< t_{\varphi_k}, i_{\varphi_k}, f_{\varphi_k} > (k = 1, 2, \cdots, p)$ be a set of SVNNs. Then, the SVNN Weighted Geometric Aggregation (SVNNWGA) operator [10] is defined as

$$\begin{aligned} & SVNNWGA(\varphi_1, \varphi_2, \cdots, \varphi_p) \\ = \ & \sum_{k=1}^{p} \gamma_k \varphi_k = \langle \Pi_{k=1}^{p} (t_{\varphi_k})^{\gamma_k}, 1 - \Pi_{k=1}^{p} (1 - i_{\varphi_k})^{\gamma_k}, 1 - \Pi_{k=1}^{p} (1 - f_{\varphi_k})^{\gamma_k} \rangle \end{aligned} \tag{2}$$

where γ_k are the weights and $\sum_{k=1}^{p} \gamma_k = 1$.

Definition 2.6 [44]: Let $\varphi_1 =< t_{\varphi_1}, i_{\varphi_1}, f_{\varphi_1} >$ and $\varphi_2 =< t_{\varphi_2}, i_{\varphi_2}, f_{\varphi_2} >$ be two SVNNs. Then the Hamming distance $d(\varphi_1, \varphi_2)$ between two SVNNs is defined as

$$d(\varphi_1, \varphi_2) = \frac{1}{3}(|t_{\varphi_1} - t_{\varphi_2}| + |i_{\varphi_1} - i_{\varphi_2}| + |f_{\varphi_1} - f_{\varphi_2}|) \tag{3}$$

3. CRITIC STRATEGY FOR SVNNs

Suppose that $N = \langle N_1, N_2, \cdots, N_r \rangle$ is a collection of r alternatives and $\hat{P} = \langle \hat{P}_1, \hat{P}_2, \cdots, \hat{P}_s \rangle$ is a collection of s attributes. The weight calculating CRITIC strategy for SVNNs is stated below:

Step 1: *Define the decision matrix.*

Suppose that $H = (h_{lm})_{r\times s}$ is the decision matrix which includes the details of the alternative N_r w.r.t the attribute P_s. The r-th decision matrix (H) is constructed as follows:

$$H = (h_{lm})_{r\times s} = \begin{pmatrix} h_{11} & h_{12} & \cdots & h_{1s} \\ h_{21} & h_{22} & \cdots & h_{2s} \\ \cdots & \cdots & \cdots & \cdots \\ h_{r1} & h_{r2} & \cdots & h_{rs} \end{pmatrix} \tag{4}$$

where $l = 1, 2, \cdots, r$ and $m = 1, 2, \cdots, s$.

Step 2: *Standardize the decision matrix([45]).*

There are typically two sorts of attributes in MADM problems: benefit attributes and cost attributes. For making standardized decision matrix, complement of the cost attribute ($h^{'}_{lm}$) is taken, and benefit attribute remains the same.

$$\begin{aligned} h_{lm} &= (t_{h_{lm}}, i_{h_{lm}}, f_{h_{lm}}) \\ h^{'}_{lm} &= (f_{h_{lm}}, 1 - i_{h_{lm}}, t_{h_{lm}}) \end{aligned} \tag{5}$$

Step 3: *Aggregate the decision matrices.*

Aggregate the decision matrices using the following formula:

$$\begin{aligned} & SVNNWGA(h_1, h_2, \cdots, h_r) \\ = & \sum_{l=1}^{r} \gamma_l h_l = \langle \Pi_{l=1}^{r}(t_l)^{\gamma_l}, 1 - \Pi_{l=1}^{r}(1 - i_l)^{\gamma_l}, 1 - \Pi_{l=1}^{r}(1 - f_l)^{\gamma_l} \rangle \end{aligned} \tag{6}$$

where γ_k is the weight of k-th the decision maker and $\sum_{l=1}^{r} \gamma_l = 1$.

Step 4: *Determine the score value each of SVNN.*

The score value $Sc(h_{lm})$ for each SVNN is obtained from the following:

$$Sc(h_{lm}) = \frac{1 + t_{h_{lm}} - 2i_{h_{lm}} - f_{h_{lm}}}{2}, \quad -1 \leq Sc(h_{lm}) \leq 1 \tag{7}$$

Here $l = 1, 2, \cdots, r$ and $m = 1, 2, \cdots, s$.

Step 5: The sample standard deviation σ_m of each attribute is calculated as

$$\sigma_m = \sqrt{\frac{1}{s-1} \sum_{m=1}^{s} (h_{lm} - \bar{h}_m)^2}, \quad l = 1, 2, \cdots, r. \tag{8}$$

Step 6: *Correlation coefficient.*

The correlation coefficient (ζ_{mn}) between the attributes is determined as follows:

$$\zeta_{mn} = \frac{\sum_{l=1}^{r}(h_{lm} - \bar{h}_m)(h_{ln} - \bar{h}_n)}{\sqrt{\sum_{l=1}^{r}(h_{lm} - \bar{h}_m)^2 (h_{ln} - \bar{h}_n)^2}} \tag{9}$$

where $\bar{h}_m$ and $\bar{h}_n$ are the means of m-th and n-th attributes. $\bar{h}_m$ is evaluated as

$$\bar{h}_m = \frac{1}{s}\sum_{m=1}^{s} h_{lm}, \quad m = 1, 2, \cdots, s. \tag{10}$$

Step 7: The index (C) is determined as [1]

$$C_m = \sigma_m \sum_{n=1}^{s}(1 - \zeta_{mn}). \tag{11}$$

Step 8: The following formula is used to determine the weights (ν_m) of the attributes:

$$\nu_m = \frac{C_m}{\sum_{m=1}^{s} C_m} \tag{12}$$

The above steps are summarised in Figure 1.

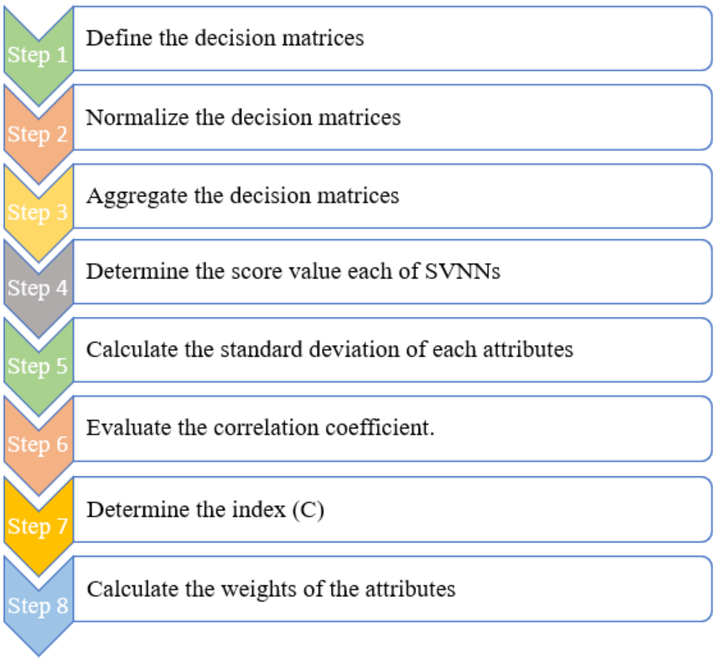

Figure 1: CRITIC strategy for SVNNs

4. CRITIC-EDAS STRATEGY FOR SVNSs

Assume that $N = \langle N_1, N_2, \cdots, N_r\rangle$ is a collection of r alternatives and $\hat{P} = \langle \hat{P}_1, \hat{P}_2, \cdots, \hat{P}_s\rangle$ is a collection of s attributes.

Steps 1- 8 are same as CRITIC strategy.
Step 9: *Evaluate the average solution(AS) of attributes.*
Calculate the Average Solution (h_m^*) of the attributes as given below:

$$h_m^* = < t_m^*, i_m^*, f_m^* > \quad \text{where} \tag{13}$$

$$t_m^* = \frac{\sum_{l=1}^r t_{lm}}{r}, i_m^* = \frac{\sum_{l=1}^r i_{lm}}{r}, f_m^* = \frac{\sum_{l=1}^r f_{lm}}{r} \quad \text{for all } h_{lm} \in H.$$

Step 10: *Determine the Positive Distance Average Solution (PDAS) and the Negative Distance Average Solution (NDAS).*
Evaluate the PDAS (d_{lm}^+) and NDAS (d_{lm}^-) from the average as follows:

$$d_{lm}^+ =< \frac{max(0,(t_{lm}-t_m^*)}{h_m^*}, \frac{max(0,(i_{lm}-i_m^*)}{h_m^*}, \frac{max(0,(f_{lm}-f_m^*)}{h_m^*} > \tag{14}$$

$$d_{lm}^- =< \frac{max(0,(t_m^*-t_{lm})}{h_m^*}, \frac{max(0,(i_m^*-i_{lm})}{h_m^*}, \frac{max(0,(f_m^*-f_{lm})}{h_m^*} > \tag{15}$$

where $h_l^* = max(\frac{\sum_{l=1}^r t_{lm}}{r}, \frac{\sum_{l=1}^r i_{lm}}{r}, \frac{\sum_{l=1}^r f_{lm}}{r})$
For the benefit attribute, PDAS is used, while for the cost attribute, NDAS is used.
Step 11: *Evaluate the weighted PDAS and NDAS .*
Suppose that $\nu = (\nu_1, \nu_2, \cdots, \nu_s)$ is a set of non-negative weights. Calculate the weighted sum of PDAS(ζ_l^+), and NDAS(ζ_l^-) for all alternatives as follows:

$$\zeta_l^+ = \sum_{m=1}^{s} \nu_m d_{lm}^+ = \langle \Pi_{m=1}^s (t_m)^{\nu_m}, 1-\Pi_{m=1}^s (1-i_m)^{\nu_m}, 1-\Pi_{m=1}^s (1-f_m)^{\nu_m} \rangle \tag{16}$$

$$\zeta_l^- = \sum_{m=1}^{s} \nu_m d_{lm}^- = \langle \Pi_{m=1}^s (t_m)^{\nu_m}, 1-\Pi_{m=1}^s (1-i_m)^{\nu_m}, 1-\Pi_{m=1}^s (1-f_m)^{\nu_m} \tag{17}$$

and evaluate the score values of the obtained results.
Step 12: *Normalize ζ_l^+ and ζ_l^- for all the alternatives.*
Normalize the ζ_l^+ and ζ_l^- for each of the alternatives as follows:

$$S_l^+ = \frac{\zeta_l^+}{max\zeta_n^+} \tag{18}$$

$$S_l^- = 1 - \frac{\zeta_l^-}{max\zeta_n^-} \tag{19}$$

Here, $l = 1, 2, \cdots, r$ and S_l^+, and S_l^- represent the normalized weighted sums of the PDAS and the NDAS, respectively.
Step 13: *Evaluate each alternative's Appraisal Score (S_l).*
The S_l is defined by

$$S_l = \frac{1}{2}(S_l^+ + S_l^-) \quad (l = 1, 2, \cdots, r) \tag{20}$$

Step 14: Rank the options according to the decreasing values of appraisal scores. The best alternative is the one with the highest appraisal score.
The above steps are summarised in Figure 2.

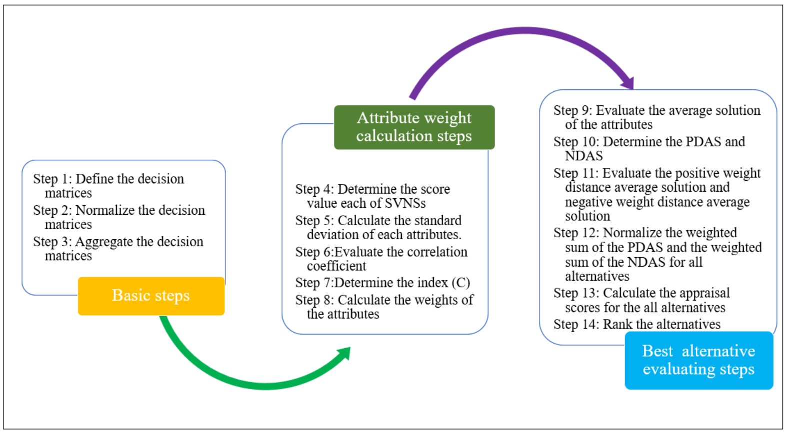

Figure 2: CRITIC-EDAS strategy for SVNNs

5. ILLUSTRATIVE EXAMPLE

In this section, we present a realistic example to demonstrate the viability of the proposed strategies.The importance of choosing the right job route is growing for B.Com students today. Students must take into account a range of considerations when selecting a career. A student's choice may be influenced by a variety of factors, including parents, coaches, and any role models in their lives. This is an MAGDM problem, and we apply the proposed strategies to select the optimal alternative for the students. We consider four alternatives and five attributes. The alternatives are: (1) Higher Education (N_1) (2) Starting a Business (N_2) (3) Professional course join (N_3) (MBA, Chartered Accountancy, Chartered Financial Analyst, Business Accounting and Taxation, Certified Management Accountant, Certified Public Accounting, Certified Financial Planner)(4) Job (N_4)(Company Secretary), and the attributes are: (1) Interest in the field ($\hat{P}_1$) (2) Academic Ability and Aptitude ($\hat{P}_2$) (3) Personality ($\hat{P}_3$) (4) Cost related to the alternative ($\hat{P}_4$)(5) Growth potentiality ($\hat{P}_5$).
Here, Interest in the field ($\hat{P}_1$), Academic Ability and Aptitude ($\hat{P}_2$), Personality($\hat{P}_3$) and Growth potentiality ($\hat{P}_5$) are benefit type attributes and Cost related to the alternative ($\hat{P}_4$) is cost type attribute.

The weights of the attributes are $(\nu_1, \nu_2, \nu_3, \nu_4, \nu_5)$ and these weights are calculated using CRITIC strategy. The guardians of the students hire three decision makers: (1) expert on B.Com. field $\hat{S}^1$, (2) career counsellor $\hat{S}^2$ and (3) students' favourite teacher $\hat{S}^3$, and weights of the decision makers are (.45, .25, .3).

5.1. CRITIC strategy for SVNSs

We construct the following decision matrices and proceed to do the calculations according to the steps outlined in Section 4.

Step 1: We construct the decision matrices given in Table 1.

Table 1: Decision matrices

	Alternative	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_3$	$\hat{P}_4$	$\hat{P}_5$
	N_1	$\langle .64, .52, .45\rangle$	$\langle .81, .76, .35\rangle$	$\langle .76, .21, .18\rangle$	$\langle .84, .32, .21\rangle$	$\langle .68, .35, .33\rangle$
$\hat{S}^1$	N_2	$\langle .72, .42, .35\rangle$	$\langle .52, .30, .25\rangle$	$\langle .85, .48, .39\rangle$	$\langle .77, 0.3, .22\rangle$	$\langle .60, .55, .36\rangle$
	N_3	$\langle .70, .31, .27\rangle$	$\langle .86, .30, .22\rangle$	$\langle .65, .45, .38\rangle$	$\langle .84, .65, .25\rangle$	$\langle .68, .29, .26\rangle$
	N_4	$\langle .28, .60, .62\rangle$	$\langle .66, .31, .3\rangle$	$\langle .18, .28, .87\rangle$	$\langle .22, .30, .82\rangle$	$\langle .40, .21, .55\rangle$
	N_1	$\langle .55, .39, .45\rangle$	$\langle .72, .33, .30\rangle$	$\langle .82, .25, .15\rangle$	$\langle .82, .33, .21\rangle$	$\langle .69, .32, .29\rangle$
$\hat{S}^2$	$\hat{N}_2$	$\langle .72, .63, .31\rangle$	$\langle .81, .27, .24\rangle$	$\langle .75, .49, .39\rangle$	$\langle .71, 0.35, .25\rangle$	$\langle .51, .38, .36\rangle$
	N_3	$\langle .72, .34, .25\rangle$	$\langle .81, .33, .18\rangle$	$\langle .68, .45, .34\rangle$	$\langle .88, .34, .25\rangle$	$\langle .72, .19, .26\rangle$
	N_4	$\langle .60, .73, .59\rangle$	$\langle .45, .32, .3\rangle$	$\langle .3, .32, .88\rangle$	$\langle .25, .3, .81\rangle$	$\langle .62, .22, .27\rangle$
	N_1	$\langle .66, .49, .44\rangle$	$\langle .83, .64, .31\rangle$	$\langle .77, .26, .20\rangle$	$\langle .84, .32, .21\rangle$	$\langle .68, .35, .33\rangle$
$\hat{S}^3$	N_2	$\langle .72, .42, .35\rangle$	$\langle .52, .30, .25\rangle$	$\langle .85, .48, .39\rangle$	$\langle .77, 0.3, .22\rangle$	$\langle .60, .55, .36\rangle$
	N_3	$\langle .70, .31, .24\rangle$	$\langle .86, .30, .22\rangle$	$\langle .65, .45, .38\rangle$	$\langle .84, .65, .25\rangle$	$\langle .68, .29, .26\rangle$
	N_4	$\langle .28, .60.62\rangle$	$\langle .66, .31, .3\rangle$	$\langle .18, .28, .87\rangle$	$\langle .22, .30, .82\rangle$	$\langle .40, .21, .55\rangle$

Step 2: Using Eq. (5), we calculate the standardize matrices and these matrices are shown in Table 2.

Table 2: Standardize decision matrices

	Alternative	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_3$	$\hat{P}_4$	$\hat{P}_5$
	N_1	$\langle .64, .52, .45\rangle$	$\langle .81, .76, .35\rangle$	$\langle .76, .21, .18\rangle$	$\langle .21, .68, .84\rangle$	$\langle .68, .35, .33\rangle$
$\hat{S}^1$	N_2	$\langle .72, .42, .35\rangle$	$\langle .52, .30, .25\rangle$	$\langle .85, .48, .39\rangle$	$\langle .22, 0.7, .77\rangle$	$\langle .60, .55, .36\rangle$
	N_3	$\langle .70, .31, .27\rangle$	$\langle .86, .30, .22\rangle$	$\langle .65, .45, .38\rangle$	$\langle .25, .45, .84\rangle$	$\langle .68, .29, .26\rangle$
	N_4	$\langle .28, .60, .62\rangle$	$\langle .66, .31, .3\rangle$	$\langle .18, .28, .87\rangle$	$\langle .82, .70, .22\rangle$	$\langle .40, .21, .55\rangle$
	N_1	$\langle .55, .39, .45\rangle$	$\langle .72, .33, .30\rangle$	$\langle .82, .25, .15\rangle$	$\langle .77, .33, .21\rangle$	$\langle .69, .32, .29\rangle$
$\hat{S}^2$	N_2	$\langle .72, .63, .31\rangle$	$\langle .81, .27, .24\rangle$	$\langle .75, .49, .39\rangle$	$\langle .25, 0.65, .82\rangle$	$\langle .51, .38, .36\rangle$
	N_3	$\langle .72, .34, .25\rangle$	$\langle .81, .33, .18\rangle$	$\langle .68, .45, .34\rangle$	$\langle .25, .66, .88\rangle$	$\langle .72, .19, .26\rangle$
	N_4	$\langle .60, .73, .59\rangle$	$\langle .45, .32, .3\rangle$	$\langle .3, .32, .88\rangle$	$\langle .81, .70, .25\rangle$	$\langle .62, .22, .27\rangle$
	N_1	$\langle .66, .49, .44\rangle$	$\langle .83, .64, .31\rangle$	$\langle .77, .26, .20\rangle$	$\langle .21, .68, .84\rangle$	$\langle .68, .35, .33\rangle$
$\hat{S}^3$	N_2	$\langle .72, .42, .35\rangle$	$\langle .52, .30, .25\rangle$	$\langle .85, .48, .39\rangle$	$\langle .22, 0.70, .77\rangle$	$\langle .60, .55, .36\rangle$
	N_3	$\langle .70, .31, .24\rangle$	$\langle .86, .30, .22\rangle$	$\langle .65, .45, .38\rangle$	$\langle .25, .35, .84\rangle$	$\langle .68, .29, .26\rangle$
	N_4	$\langle .28, .60.62\rangle$	$\langle .66, .31, .3\rangle$	$\langle .18, .28, .87\rangle$	$\langle .82, .70, .22\rangle$	$\langle .40, .21, .55\rangle$

Step 3: Using equation (6), we can now aggregate the standard decision matrices. Table 3 provides the aggregated decision matrix.

Step 4: The score value each of SVNS is given in Table 4 and this value is calculated using Eq.(7).

Step 5: Eq.(8) is used to determine the standard deviation, and the results are given in Table 5.

Table 3: Aggregated decision matrices

	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_3$	$\hat{P}_4$	$\hat{P}_5$
N_1	$\langle .6219, .4810, .4470 \rangle$	$\langle .7923, .6496, .3259 \rangle$	$\langle .7776, .2353, .1787 \rangle$	$\langle .2906, .6151, .7615 \rangle$	$\langle .6825, .3426, .3202 \rangle$
N_2	$\langle .7200, .4817, .3402 \rangle$	$\langle .5809, .2926, .2475 \rangle$	$\langle .8238, .4825, .3900 \rangle$	$\langle .2271, .6882, .7837 \rangle$	$\langle .5761, .5125, .3600 \rangle$
N_3	$\langle .7049, .3176, .2561 \rangle$	$\langle .8472, .3076, .2102 \rangle$	$\langle .6574, .4500, .3702 \rangle$	$\langle .2500, .4872, .8511 \rangle$	$\langle .6898, .2662, .2600 \rangle$
N_4	$\langle .3388, .6374, .6127 \rangle$	$\langle .5997, .3125, .3000 \rangle$	$\langle .2045, .2902, .8726 \rangle$	$\langle .8175, .7000, .2276 \rangle$	$\langle .4463, .2125, .4921 \rangle$

Table 4: Score value of the aggregate decision matrix

	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_3$	$\hat{P}_4$	$\hat{P}_5$
N_1	.1064	.0836	.5641	-.3505	.3385
N_2	.2082	.3741	.2344	-.4665	.0956
N_3	.4148	.5109	.1936	-.2878	.4487
N_4	-.2744	.3374	-.1242	.0949	.2646

Table 5: Values of standard deviation

	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_3$	$\hat{P}_4$	$\hat{P}_5$
σ_j	.2889	.1783	.2815	.2431	.1482

Step 6: The correlation coefficient between attributes is determined by Eq. (9) and shown in Table 6.

Table 6: Correlation coefficient matrix

	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_3$	$\hat{P}_4$	$\hat{P}_5$
$\hat{P}_1$	1	.3726	.5104	-.7831	.303
$\hat{P}_2$	.3726	1	-.6077	.0837	.1002
$\hat{P}_3$	.5104	-.6077	1	-.7571	.2072
$\hat{P}_4$	-.7571	.0837	-.7571	1	.2072
$\hat{P}_5$	.3030	.1002	.2072	.2072	1

Step 7: We evaluate the index C using Eq. (11) and present in Table 7.

Table 7: Index C matrix

	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_3$	$\hat{P}_4$	$\hat{P}_5$
$\hat{P}_1$	0	.6274	.4896	1.7831	.6970
$\hat{P}_2$	.6274	0	1.6077	.9163	.8998
$\hat{P}_3$	.4896	1.6077	0	1.7571	.7928
$\hat{P}_4$	1.7831	.9163	1.7571	0	.7928
$\hat{P}_5$	.6970	.8998	.7928	.7928	0

Step 8: The weights of the attributes are determined by Eq.(12) and are given below: $\nu_1 = 0.2164, \nu_2 = 0.1500, \nu_3 = 0.2716, \nu_4 = 0.2649, \nu_5 = 0.0979$.

5.2. CRITIC-EDAS strategy for SVNSs

The previous three steps are same as CRITIC strategy.

Step 9: Using Eq. (13), we evaluate the average solution of all attributes, shown in Table 8

Table 8: Average decision matrix

	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_3$	$\hat{P}_4$	$\hat{P}_5$
N_1	$\langle .6167, .4667, .4467\rangle$	$\langle .7867, .5767, .3200\rangle$	$\langle .7833, .2400, .1767\rangle$	$\langle .3967, .5633, .6300\rangle$	$\langle .6833, .3400, .3167\rangle$
N_2	$\langle .7200, .4900, .3367\rangle$	$\langle .6167, .2900, .2467\rangle$	$\langle .8167, .4833, .3900\rangle$	$\langle .2300, .6833, .7867\rangle$	$\langle .5700, .4933, .3600\rangle$
N_3	$\langle .7067, .3200, .2533\rangle$	$\langle .8433, .3100, .2067\rangle$	$\langle .6600, .4500, .3667\rangle$	$\langle .2500, .4867, .8533\rangle$	$\langle .6933, .2567, .2600\rangle$
N_4	$\langle .3867, .6433, .6100\rangle$	$\langle .5900, .3133, .3000\rangle$	$\langle .2200, .2933, .8733\rangle$	$\langle .8167, .7000, .2300\rangle$	$\langle .4733, .2133, .4567\rangle$

for all $x_{ij} \in X$.

Step 10: Using Eq. (14) and (15), we determine the PDAS and NDAS given in Tables 9 and 10.

Table 9: Positive distance average solution

	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_3$	$\hat{P}_4$	$\hat{P}_5$
N_1	$\langle .0085, .0233, .0006\rangle$	$\langle .0071, .0928, .0075\rangle$	$\langle 0, 0, .0026\rangle$	$\langle 0, .0821, .2087\rangle$	$\langle 0, .0038, .0052\rangle$
N_2	$\langle 0, 0, .0049\rangle$	$\langle 0, .0042, .0014\rangle$	$\langle .0088, 0, 0\rangle$	$\langle 0, .0062, 0\rangle$	$\langle .0107, .0336, 0\rangle$
N_3	$\langle 0, 0, .0039\rangle$	$\langle .0046, 0, .0042\rangle$	$\langle 0, 0, .0054\rangle$	$\langle 0, .0007, 0\rangle$	$\langle 0, .0138, 0\rangle$
N_4	$\langle 0, 0, .0042\rangle$	$\langle .0165, 0, 0\rangle$	$\langle 0, 0, 0\rangle$	$\langle .0010, 0, 0\rangle$	$\langle 0, 0, .0750\rangle$

Table 10: Negative distance average solution

	$\hat{P}_1$	$\hat{P}_2$	$\hat{P}_3$	$\hat{P}_4$	$\hat{P}_5$
N_1	$\langle 0, 0, 0\rangle$	$\langle 0, 0, 0\rangle$	$\langle .0073, .0059, 0\rangle$	$\langle .1684, 0, 0\rangle$	$\langle .0012, 0, 0\rangle$
N_2	$\langle 0, .0116, 0\rangle$	$\langle .0580, 0, 0\rangle$	$\langle 0, .0010, 0\rangle$	$\langle .0036, 0, .0038\rangle$	$\langle 0, 0, 0\rangle$
N_3	$\langle .0024, .0034, 0\rangle$	$\langle 0, .0028, 0\rangle$	$\langle .0040, 0, 0\rangle$	$\langle 0, 0, .0026\rangle$	$\langle .0051, 0, 0\rangle$
N_4	$\langle .0744, .0092, 0\rangle$	$\langle 0, .0014, 0\rangle$	$\langle .0177, .0036, .0009\rangle$	$\langle 0, 0, .0029\rangle$	$\langle .0571, .0017, 0\rangle$

Step 11: We evaluate weighted sum PDAS and NDAS using Eqs. (16) and (17) as given in Table 11.

Table 11: ζ_l^+ and ζ_l^- and score value of the alternative

	ζ_l^+	*Sc. value of* ζ_l^+	ζ_l^-	*Sc. value of* ζ_l^-
N_1	$\langle 0, .0419, .0624\rangle$	0.4269	$\langle 0, .0016, 0\rangle$	.4984
N_2	$\langle 0, .0056, .0013\rangle$	.4937	$\langle 0, .0028, .0010\rangle$	.4967
N_3	$\langle 0, .0015, .0029\rangle$	.4970	$\langle 0, .0012, .0007\rangle$	.4985
N_4	$\langle 0, 0, .0085\rangle$	.4957	$\langle 0, .0033, .0010\rangle$	.4962

Step 12: Using equations (18) and (19), we normalize ζ_l^+ and ζ_l^- for all alternatives as given in Table 12.

Step 13: Using equation (20), we measure the appraisal score for each the alternatives.

$N_1 = .4296, N_2 = .4985, N_3 = .5000, N_4 = .5011$

Table 12: Normalize ζ_l^+ and ζ_l^-

	N_1	N_2	N_3	N_4
S_i^+	.8590	.9935	1	.9975
S_i^-	.0002	.0036	0	.0047

Step 14: The best alternative according to appraisal score is N_4

6. CONCLUSION

In this paper, the CRITIC and EDAS techniques are integrated which we call the CRITIC-EDAS strategy to solve the career selection problem for graduate students. The attribute weights are evaluated using the CRITIC strategy, and the alternatives are ranked using the EDAS strategy. Both strategies have their benefits and drawbacks. The CRITIC strategy assures objective attribute weight determination while ignoring the decision makers' subjective point of view, knowledge, experience, and perception of the situation. The developed strategy considers the severity of the contrast in the DM problem's structure. It follows simple computational application steps. So, the decision-makers can quickly apply them to various real-world MAGDM situations. The length of time needed to address the MAGDM problem increases when the dimension of the decision matrix increases. So, software that can implement the CRITIC-EDAS methodology may be developed in the future. Complex decision-making challenges can be handled methodically with that software. The practical implication of CRITIC- EDAS methodology can be used for solving real MAGDM problems. The limitation of the work is that it is not a case study but rather an illustration example of the career selection problem of graduate students.

In the future, we will work on diverse MAGDM strategies (namely, IDOCRIW, COCOSO, and COPRAS) to select the best carrier for graduate students in the SVNS environment. Also, we will implement the developed framework in the different MAGDM problems, namely, the selection of digital image forensic tools, green supplier selection and teacher selection. Without loss of generality, the developed framework can be extended to other extended neutrosophic environments such as pentapartitioned neutrosophic sets [46].

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