Multi-criteria group decision making approach based on a new type of neutrosophic vague approach is used to select the shares of the companies for purchase

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Abstract

In this paper, we introduce the neutrosophic vague soft set, a combination of vague and neutrosophic soft sets. With the help of aggregated operations, we discuss neutrosophic vague soft sets. Multi-criteria group decision making can be evaluated effectively using the VIKOR approach. In this approach, the score function is generated by aggregating the VIKOR method to a neutrosophic vague soft approach. With the help of closeness values, alternative solutions are presented as optimal ones. To invest some money into the top five companies on the stock exchange, an investment company intends to purchase shares of the companies. Their investment strategy was to allocate some of their cash in percentages of 30 dollars, 25 dollars, 20 dollars, 15 dollars, and 10 dollars according to the top five ranked companies to minimize this effect.

Keywords: NVS set; MCGDM; VIKOR; aggregation operator.

1 Introduction

Decision-makers are having a hard time identifying optimal solutions to real-world systems because they are becoming increasingly complex. There is still the possibility of choosing the most suitable option despite the difficulty of choosing between the alternatives. A number of firms have difficulty creating opportunities, objectives, and constraints based on their viewpoints. The decision-making (DM) process should consider both individuals and groups of objectives simultaneously. There are many different issues that are related to MADM that are dealt with on a daily basis. The result of this is that we need to improve our DM abilities as a

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result. Decision making involves deciding among options what is the most appropriate alternative. Hwang et al.[1] that the use of multiple criteria decision making (MCDM) can be beneficial. MCDM problem expressed as a matrix

$$\Theta_{m\times n} = \begin{array}{c} \\ \Xi_1 \\ \Xi_2 \\ \vdots \\ \Xi_m \end{array} \begin{array}{c} \begin{array}{cccc} \Theta_1 & \Theta_2 & \dots & \Theta_n \end{array} \\ \begin{pmatrix} \zeta_{11} & \zeta_{12} & \cdots & \zeta_{1n} \\ \zeta_{21} & \zeta_{22} & \cdots & \zeta_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \zeta_{m1} & \zeta_{m2} & \cdots & \zeta_{mn} \end{pmatrix} \end{array}$$

where $\Xi_1, \Xi_2, ..., \Xi_m$ are alternatives and $\Theta_1, \Theta_2, ..., \Theta_n$ are criteria and ζ_{ij} is the rating of Ξ_i to Θ_j. For MAGDM problems under uncertain environments, Xiao et al.[2] investigated a fuzzy soft set area with interval values. A variety of methods have been used by researchers to study this field. For dealing with uncertainties, they propose several uncertain theories, including fuzzy set (FS),[3] intuitionistic fuzzy set (IFS),[4] interval valued set (IVFS),[5] vague set,[6] Pythagorean set (PFS),[7] IVPFS,[8] and spherical set (SFS).[9] From 0 to 1, membership grades (MGs) indicate how well a FS fits into the specified set. By Atanassov,[4] an IFS is defined as a grade less than one for both MGS and non-membership grades (NMGs). When a DM method is applied, the sum of MG and NMG can be greater than one. Yager of[7] deals the square sum of the MG and NMG of PFS is greater than one. Yager built a model using PFS to generalize IFS.

The lack of favoritism or disfavor does not demonstrate neutrality. A total grade of one was given to each of three pointers, including positive, neutral, and negative, by Cuong et al.[10] For selective applications, this set should be preferred over IFS or PFS by the DM method.[11–16] A generalized PFS aggregation operator (AO) was first presented by Liu et al.[17] It is shown that AOs[8, 18–20] have the feature that the sum of the three grades (TMG, IMG, and FMG) exceeds one in identifying truth membership grades (TMGs), indeterminacy membership grades (IMGs), and false membership grades (FMGs). It has been suggested by Ashraf et al.[9] that the SFS should contain the following graph: this diagram shows that the sum of the squares of the TMG, IMG and FMG should be not exceeds one. An application of Pythagorean fuzzy soft set theory to real life was discussed by Peng et al.[21] in 2015. Recent studies on complex Pythagorean FSs using pattern recognition by Ullah et al.[22] Recently, Palanikumar et al.[23,24] discussed many AOs based on Neutrosphic logic, SFSs, soft sets are introduced.

This article is argued to extend the MCDM techniques used to describe Pythagorean fuzzy soft sets under VIKOR to NVS sets under VIKOR and to derive some of the properties from those. In accordance with that, the paper is divided into four sections, which are summarized below. Section 1 provides a brief introduction. In Section 2, NVS set is briefly described. A discussion of MCGDM based on NVS-VIKOR using AO is provided in the section 3. The section 4 includes a conclusion.

2 Preliminaries

Definition 2.1. Let L be a PIVFS in $\mathbb{U}$ is of the form $\widetilde{L} = \left\{\vartheta, \left\langle \widetilde{\gamma_L^T}(\vartheta), \widetilde{\gamma_L^F}(\vartheta)\right\rangle \Big| \vartheta \in \mathbb{U}\right\}$, $\widetilde{\gamma_L^T}(\vartheta) = \left[\gamma_L^{Tl}(\vartheta), \gamma_L^{Tu}(\vartheta)\right]$ and $\widetilde{\gamma_L^F}(\vartheta) = \left[\gamma_L^{Fl}(\vartheta), \gamma_L^{Fu}(\vartheta)\right]$ denotes the membership degree and non-membership degree of L respectively. Here $\widetilde{\gamma_L^T}$ and $\widetilde{\gamma_L^F}$ are function from $\mathbb{U}$ into $\mathbb{D}[0,1]$ and $0 \le (\widetilde{\gamma_L^T}(\vartheta))^2 + (\widetilde{\gamma_L^F}(\vartheta))^2 \le 1$ it is observed that $0 \le (\gamma_L^{Tu}(\vartheta))^2 + (\gamma_L^{Fu}(\vartheta))^2 \le 1$.

Definition 2.2. The neutrosophic set (NS) $L = \left\{\vartheta, \langle \gamma_L^T(\vartheta), \gamma_L^I(\vartheta), \gamma_L^F(\vartheta)\rangle \big| \vartheta \in \mathbb{U}\right\}$, where $\gamma_L^T(\vartheta)$, $\gamma_L^I(\vartheta)$ and $\gamma_L^F(\vartheta)$ are called TG, IG and FG of L respectively. Here γ_L^T, γ_L^I and γ_L^F are function from $\mathbb{U}$ into $[0,1]$ and $0 \le \gamma_L^T(\vartheta) + \gamma_L^I(\vartheta) + \gamma_L^F(\vartheta) \le 3$.

Definition 2.3. The neutrosophic interval valued set $\widetilde{L} = \left\{\vartheta, \left(\widetilde{\chi_L^T}(\vartheta), \widetilde{\chi_L^I}(\vartheta), \widetilde{\chi_L^F}(\vartheta)\right) | \vartheta \in \mathbb{U}\right\}$, where $\widetilde{\chi_L^T}(\vartheta) = \left[\chi_L^{Tl}(\vartheta), \chi_L^{Tu}(\vartheta)\right]$, $\widetilde{\chi_L^I}(\vartheta) = \left[\chi_L^{Il}(\vartheta), \chi_L^{Iu}(\vartheta)\right]$ and $\widetilde{\chi_L^F}(\vartheta) = \left[\chi_L^{Fl}(\vartheta), \chi_L^{Fu}(\vartheta)\right]$ represents the degree of truth, indeterminacy and falsity-membership of L respectively. Consider the mapping $\widetilde{\chi_L^T} : \mathbb{U} \to D[0,1]$, $\widetilde{\chi_L^I} : \mathbb{U} \to D[0,1]$, $\widetilde{\chi_L^F} : \mathbb{U} \to D[0,1]$ and $0 \le (\widetilde{\chi_L^T}(\vartheta))^2 + (\widetilde{\chi_L^I}(\vartheta))^2 + (\widetilde{\chi_L^F}(\vartheta))^2 \le 2$. Here $\widetilde{L} = \left(\left[\chi_L^{Tl}, \chi_L^{Tu}\right], \left[\chi_L^{Il}, \chi_L^{Iu}\right], \left[\chi_L^{Fl}, \chi_L^{Fu}\right]\right)$ is called a Pythagorean neutrosophic interval valued number (PyNIVN).

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Definition 2.4. Let $\mathbb{U}$ and E be the universe and set of parameter respectively. The pair $\widetilde{(\Gamma, L)}$ or $\widetilde{\Gamma_L}$ is called a PyNIVFS set on $\mathbb{U}$ if $L \sqsubseteq E$ and $\Gamma : L \to PyNIVF^{\mathbb{U}}$, $PyNIVF^{\mathbb{U}}$ is denote the set of all Pythagorean neutrosophic interval valued fuzzy subsets of $\mathbb{U}$. That is
$$\widetilde{\Gamma_L} = \left\{ \left(e, \left\{ \frac{x}{\left(\left[\chi^{Tl}_{\Gamma_L}(\vartheta), \chi^{Tu}_{\Gamma_L}(\vartheta)\right], \left[\chi^{Il}_{\Gamma_L}(\vartheta), \chi^{Iu}_{\Gamma_L}(\vartheta)\right], \left[\chi^{Fl}_{\Gamma_L}(\vartheta), \chi^{Fu}_{\Gamma_L}(\vartheta)\right] \right)} \right\} \right) : e \in L, \vartheta \in \mathbb{U} \right\}.$$

Remark 2.5. Using fundamental operations of arithmetic leads to the following.
(i) $[u, v] + [w, x] = [u + w, v + x]$
(ii) $[u, v] - [w, x] = [u - \vartheta, v - w]$
(iii) $[u, v] \cdot [w, x] = [uw, vx]$, whenever $u \geq 0$ and $v \geq 0$
(iv) $\frac{1}{[u,v]} = [\frac{1}{v}, \frac{1}{u}]$, whenever $0 \notin [u, v]$, $u, v, w, \vartheta \in \mathbb{R}$.

Definition 2.6. (i) The VS L in $\mathbb{U}$ is a pair (T_L, F_L), $T_L, F_L : \mathbb{U} \to [0, 1]$ are mappings that $T_L(\vartheta) + F_L(\vartheta) \preceq 1$, for all $\vartheta \in \mathbb{U}$, T_L and F_L are presents TMG and FMG respectively.
(ii) $L_L(\vartheta) = [T_L(\vartheta), 1 - F_L(\vartheta)]$ is called the vague value of ϑ in L.

Definition 2.7. (i) A VS L is contained in the other VS $L^{'}$, $L \subseteq L^{'}$ if and only if $L_L(\vartheta) \preceq L_{L'}(\vartheta)$. That is, $T_L(\vartheta) \preceq T_{L'}(\vartheta)$ and $1 - F_L(\vartheta) \preceq 1 - F_{L'}(\vartheta)$, for all $\vartheta \in \mathbb{U}$.
(ii) $\mathbb{U} = L \cup L^{'}$, $T_{\mathbb{U}} = max\{T_L, T_{L'}\}$ and $1 - F_{\mathbb{U}} = max\{1 - F_L, 1 - F_{L'}\} = 1 - min\{F_L, F_{L'}\}$.
(iii) $\mathbb{U} = L \cap L^{'}$, $T_{\mathbb{U}} = min\{T_L, T_{L'}\}$ and $1 - F_{\mathbb{U}} = min\{1 - F_L, 1 - F_{L'}\} = 1 - max\{F_L, F_{L'}\}$.

Definition 2.8. The VS L of $\mathbb{U}$, for all $\vartheta \in \mathbb{U}$. Then
(i) $T_L(\vartheta) = 0$ and $F_L(\vartheta) = 1$ is represent zero VS of $\mathbb{U}$.
(ii) $T_L(\vartheta) = 1$ and $F_L(\vartheta) = 0$ is represent unit VS of $\mathbb{U}$.

3 NVS-VIKOR using AO

Algorithm (NVS-VIKOR)

Step-1: Suppose that $\Theta = \{\Theta_i : i \in \mathbb{N}\}$ be the decision makers, $\mathscr{C} = \{\zeta_i : i \in \mathbb{N}\}$ be the alternatives and $D = \{e_i : i \in \mathbb{N}\}$ is a parameters.
Step-2: Determine the weighted parameter matrix and linguistic variables

$$\mathcal{P} = \left[\varsigma^l_{ij}, \varsigma^u_{ij}\right]_{n \times m} = \begin{bmatrix} [\varsigma^l_{11}, \varsigma^u_{11}] & [\varsigma^l_{12}, \varsigma^u_{12}] & \cdots & [\varsigma^l_{1m}, \varsigma^u_{1m}] \\ [\varsigma^l_{21}, \varsigma^u_{21}] & [\varsigma^l_{22}, \varsigma^u_{22}] & \cdots & [\varsigma^l_{2m}, \varsigma^u_{2m}] \\ \vdots & \vdots & \ddots & \vdots \\ [\varsigma^l_{i1}, \varsigma^u_{i1}] & [\varsigma^l_{i2}, \varsigma^u_{i2}] & \cdots & [\varsigma^l_{im}, \varsigma^u_{im}] \\ \vdots & \vdots & \ddots & \vdots \\ [\varsigma^l_{n1}, \varsigma^u_{n1}] & [\varsigma^l_{n2}, \varsigma^u_{n2}] & \cdots & [\varsigma^l_{nm}, \varsigma^u_{nm}] \end{bmatrix}$$

where $\left[\varsigma^l_{ij}, \varsigma^u_{ij}\right]$ is the weight and assigned to the expert Θ_i to e_j.
Step-3: Form the weighted normalized decision matrix as

$$\widehat{\mathcal{N}} = \left[\widehat{\eta}^l_{ij}, \widehat{\eta}^u_{ij}\right]_{n \times m} = \begin{bmatrix} [\widehat{\eta}^l_{11}, \widehat{\eta}^u_{11}] & [\widehat{\eta}^l_{12}, \widehat{\eta}^u_{12}] & \cdots & [\widehat{\eta}^l_{1m}, \widehat{\eta}^u_{1m}] \\ [\widehat{\eta}^l_{21}, \widehat{\eta}^u_{21}] & [\widehat{\eta}^l_{22}, \widehat{\eta}^u_{22}] & \cdots & [\widehat{\eta}^l_{2m}, \widehat{\eta}^u_{2m}] \\ \vdots & \vdots & \ddots & \vdots \\ [\widehat{\eta}^l_{i1}, \widehat{\eta}^u_{i1}] & [\widehat{\eta}^l_{i2}, \widehat{\eta}^u_{i2}] & \cdots & [\widehat{\eta}^l_{im}, \widehat{\eta}^u_{im}] \\ \vdots & \vdots & \ddots & \vdots \\ [\widehat{\eta}^l_{n1}, \widehat{\eta}^u_{n1}] & [\widehat{\eta}^l_{n2}, \widehat{\eta}^u_{n2}] & \cdots & [\widehat{\eta}^l_{nm}, \widehat{\eta}^u_{nm}] \end{bmatrix}$$

Here $\left[\widehat{\eta}^l_{ij}, \widehat{\eta}^u_{ij}\right] = \left[\frac{\varsigma^l_{ij}}{\sqrt{\sum_{i=1}^n \varsigma^{2u}_{ij}}}, \frac{\varsigma^u_{ij}}{\sqrt{\sum_{i=1}^n \varsigma^{2l}_{ij}}}\right]$ is the normalized criteria and find the weighted vector $\mathcal{W} = \left([m^l_1, m^u_1], [m^l_2, m^u_2]..., [m^l_m, m^u_m]\right)$, where $[m^l_i, m^u_i] = \left[\frac{\varsigma^l_i}{\sqrt{\sum_{l=1}^n \varsigma^u_{li}}}, \frac{\varsigma^u_i}{\sqrt{\sum_{l=1}^n \varsigma^l_{li}}}\right]$ mean relative weight of the

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j^{Th} parameter and $[\varsigma_j^l, \varsigma_j^u] = \left[\frac{\sum_{i=1}^{n} \widehat{\eta}_{ij}^l}{n}, \frac{\sum_{i=1}^{n} \widehat{\eta}_{ij}^u}{n} \right]$.

Step-4: The NVS decision matrix is given by

$$\Theta_i = \left[\varrho_{jk}^{li}, \varrho_{jk}^{ui}\right]_{l\times m}$$

$$= \begin{bmatrix} \left[(\varrho_{11}^T, \varrho_{11}^{1-F}), (\varrho_{11}^I, \varrho_{11}^I), (\varrho_{11}^F, \varrho_{11}^{1-T})\right]_i & \left[(\varrho_{12}^T, \varrho_{12}^{1-F}), (\varrho_{12}^I, \varrho_{12}^I), (\varrho_{12}^F, \varrho_{12}^{1-T})\right]_i & \cdots & \left[(\varrho_{1m}^T, \varrho_{1m}^{1-F}), (\varrho_{1m}^I, \varrho_{1m}^I), (\varrho_{1m}^F, \varrho_{1m}^{1-T})\right]_i \\ \left[(\varrho_{21}^T, \varrho_{21}^{2-F}), (\varrho_{21}^I, \varrho_{21}^I), (\varrho_{21}^F, \varrho_{21}^{2-T})\right]_i & \left[(\varrho_{22}^T, \varrho_{22}^{2-F}), (\varrho_{22}^I, \varrho_{22}^I), (\varrho_{22}^F, \varrho_{22}^{2-T})\right]_i & \cdots & \left[(\varrho_{2m}^T, \varrho_{2m}^{2-F}), (\varrho_{2m}^I, \varrho_{2m}^I), (\varrho_{2m}^F, \varrho_{2m}^{2-T})\right]_i \\ \vdots & \vdots & \ddots & \vdots \\ \left[(\varrho_{j1}^T, \varrho_{j1}^{j-F}), (\varrho_{j1}^I, \varrho_{j1}^I), (\varrho_{j1}^F, \varrho_{j1}^{j-T})\right]_i & \left[(\varrho_{j2}^T, \varrho_{j2}^{j-F}), (\varrho_{j2}^I, \varrho_{j2}^I), (\varrho_{j2}^F, \varrho_{j2}^{j-T})\right]_i & \cdots & \left[(\varrho_{jm}^T, \varrho_{jm}^{j-F}), (\varrho_{jm}^I, \varrho_{jm}^I), (\varrho_{jm}^F, \varrho_{jm}^{j-T})\right]_i \\ \vdots & \vdots & \ddots & \vdots \\ \left[(\varrho_{l1}^T, \varrho_{l1}^{l-F}), (\varrho_{l1}^I, \varrho_{l1}^I), (\varrho_{l1}^F, \varrho_{l1}^{l-T})\right]_i & \left[(\varrho_{l2}^T, \varrho_{l2}^{l-F}), (\varrho_{l2}^I, \varrho_{l2}^I), (\varrho_{l2}^F, \varrho_{l2}^{l-T})\right]_i & \cdots & \left[(\varrho_{lm}^T, \varrho_{lm}^{l-F}), (\varrho_{lm}^I, \varrho_{lm}^I), (\varrho_{lm}^F, \varrho_{lm}^{l-T})\right]_i \end{bmatrix}$$

where $\left[\varrho_{jk}^{li}, \varrho_{jk}^{ui}\right]$ represents i^{Th} decision maker $[\Theta_i^l, \Theta_i^u]$ for each i. The aggregating matrix $\left[\Lambda^l, \Lambda^u\right] = \frac{\left[\Theta_1^l, \Theta_1^u\right] + \left[\Theta_2^l, \Theta_2^u\right] + \ldots + \left[\Theta_n^l, \Theta_n^u\right]}{n} = \left[x_{jk}^l, x_{jk}^u\right]_{l\times m}$.

Step-5: Find the weighted NVS decision matrix

$$[\Psi^l, \Psi^u] = \left[\zeta_{jk}^l, \zeta_{jk}^u\right]_{l\times m}$$

$$= \begin{bmatrix} \left[(\zeta_{11}^T, \zeta_{11}^{1-F}), (\zeta_{11}^I, \zeta_{11}^I), (\zeta_{11}^F, \zeta_{11}^{1-T})\right] & \left[(\zeta_{12}^T, \zeta_{12}^{1-F}), (\zeta_{12}^I, \zeta_{12}^I), (\zeta_{12}^F, \zeta_{12}^{1-T})\right] & \cdots & \left[(\zeta_{1m}^T, \zeta_{1m}^{1-F}), (\zeta_{1m}^I, \zeta_{1m}^I), (\zeta_{1m}^F, \zeta_{1m}^{1-T})\right] \\ \left[(\zeta_{21}^T, \zeta_{21}^{2-F}), (\zeta_{21}^I, \zeta_{21}^I), (\zeta_{21}^F, \zeta_{21}^{2-T})\right] & \left[(\zeta_{22}^T, \zeta_{22}^{2-F}), (\zeta_{22}^I, \zeta_{22}^I), (\zeta_{22}^F, \zeta_{22}^{2-T})\right] & \cdots & \left[(\zeta_{2m}^T, \zeta_{2m}^{2-F}), (\zeta_{2m}^I, \zeta_{2m}^I), (\zeta_{2m}^F, \zeta_{2m}^{2-T})\right] \\ \vdots & \vdots & \ddots & \vdots \\ \left[(\zeta_{j1}^T, \zeta_{j1}^{j-F}), (\zeta_{j1}^I, \zeta_{j1}^I), (\zeta_{j1}^F, \zeta_{j1}^{j-T})\right] & \left[(\zeta_{j2}^T, \zeta_{j2}^{j-F}), (\zeta_{j2}^I, \zeta_{j2}^I), (\zeta_{j2}^F, \zeta_{j2}^{j-T})\right] & \cdots & \left[(\zeta_{jm}^T, \zeta_{jm}^{j-F}), (\zeta_{jm}^I, \zeta_{jm}^I), (\zeta_{jm}^F, \zeta_{jm}^{j-T})\right] \\ \vdots & \vdots & \ddots & \vdots \\ \left[(\zeta_{l1}^T, \zeta_{l1}^{l-F}), (\zeta_{l1}^I, \zeta_{l1}^I), (\zeta_{l1}^F, \zeta_{l1}^{l-T})\right] & \left[(\zeta_{l2}^T, \zeta_{l2}^{l-F}), (\zeta_{l2}^I, \zeta_{l2}^I), (\zeta_{l2}^F, \zeta_{l2}^{l-T})\right] & \cdots & \left[(\zeta_{lm}^T, \zeta_{lm}^{l-F}), (\zeta_{lm}^I, \zeta_{lm}^I), (\zeta_{lm}^F, \zeta_{lm}^{l-T})\right] \end{bmatrix}$$

where $\left[\zeta_{jk}^l, \zeta_{jk}^u\right] = \left[m_k^l \times x_{jk}^l, m_k^u \times x_{jk}^u\right]$.

Step-6: Calculate the values for NVS-PIS and NVS-NIS. Now,

NVS-PIS $= \left([\zeta_1^{l+}, \zeta_1^{u+}], [\zeta_2^{l+}, \zeta_2^{u+}] \ldots, [\zeta_l^{l+}, \zeta_l^{u+}]\right)$

$= \left\{ \left(\vee_k[\zeta_{jk}^l, \zeta_{jk}^u], \wedge_k[\zeta_{jk}^l, \zeta_{jk}^u], \wedge_k[\zeta_{jk}^l, \zeta_{jk}^u]\right) : j = 1, 2, \ldots, l\right\}$ and

NVS-PIS $= \left([\zeta_1^{l-}, \zeta_1^{u-}], [\zeta_2^{l-}, \zeta_2^{u-}] \ldots, [\zeta_l^{l-}, \zeta_l^{u-}]\right)$

$= \left\{ \left(\wedge_k[\zeta_{jk}^l, \zeta_{jk}^u], \vee_k[\zeta_{jk}^l, \zeta_{jk}^u], \vee_k[\zeta_{jk}^l, \zeta_{jk}^u]\right) : j = 1, 2, \ldots, l\right\}$.

Here NVS union $\vee$ and NVS intersection $\wedge$.

Step-7: Determine the values of utility $[\mathbb{S}_i^l, \mathbb{S}_i^u]$, individual regret $[\mathbb{R}_i^l, \mathbb{R}_i^u]$ and compromise $\mathbb{Q}_i$, where $[\mathbb{S}_i^l, \mathbb{S}_i^u] = \left[\sum_{j=1}^{m} m_j^l \cdot \left(\sqrt{\frac{(\zeta_{ij}^l - \zeta_j^{u+})^2}{(\zeta_j^{u+} - \zeta_j^{l-})^2}}\right), \sum_{j=1}^{m} m_j^u \cdot \left(\sqrt{\frac{(\zeta_{ij}^u - \zeta_j^{l+})^2}{(\zeta_j^{l+} - \zeta_j^{u-})^2}}\right)\right]$

and $[\mathbb{R}_i^l, \mathbb{R}_i^u] = \left[\max_{j=1}^{m} m_j^l \cdot \left(\sqrt{\frac{(\zeta_{ij}^l - \zeta_j^{u+})^2}{(\zeta_j^{u+} - \zeta_j^{l-})^2}}\right), \max_{j=1}^{m} m_j^u \cdot \left(\sqrt{\frac{(\zeta_{ij}^u - \zeta_j^{l+})^2}{(\zeta_j^{l+} - \zeta_j^{u-})^2}}\right)\right]$

and $\mathbb{Q}_i = \frac{\kappa\left(\frac{\mathbb{S}_i^l - \mathbb{S}^{u-}}{\mathbb{S}^{u+} - \mathbb{S}^{l-}}\right) + \kappa\left(\frac{\mathbb{S}_i^u - \mathbb{S}^{l-}}{\mathbb{S}^{l+} - \mathbb{S}^{u-}}\right) + (1-\kappa)\left(\frac{\mathbb{R}_i^l - \mathbb{R}^{u-}}{\mathbb{R}^{u+} - \mathbb{R}^{l-}}\right) + (1-\kappa)\left(\frac{\mathbb{R}_i^u - \mathbb{R}^{l-}}{\mathbb{R}^{l+} - \mathbb{R}^{u-}}\right)}{2}$.

where $[\mathbb{S}_i^{l+}, \mathbb{S}_i^{u+}] = \max_i[\mathbb{S}_i^l, \mathbb{S}_i^u]$, $[\mathbb{S}_i^{l-}, \mathbb{S}_i^{u-}] = \min_i[\mathbb{S}_i^l, \mathbb{S}_i^u]$, $[\mathbb{R}_i^{l+}, \mathbb{R}_i^{u+}] = \max_i[\mathbb{R}_i^l, \mathbb{R}_i^u]$ and $[\mathbb{R}_i^{l-}, \mathbb{R}_i^{u-}] = \min_i[\mathbb{R}_i^l, \mathbb{R}_i^u]$. A coefficient of decision mechanism is the real number κ. It has been found that the role of κ in compromise solution (CS) is to determine whether CSs can be majority. If $\kappa > 0.5$, majority solutions can be consensus. If $\kappa = 0.5$, and veto solutions can be CSs, where $[m_j^l, m_j^u]$ denotes weight of the j^{Th} parameter.

Step-8: Ranking the choices will yield a CS. You should arrange the ranking list in increasing order of $\mathbb{Q}_i$. In the case of $\mathbb{Q}_i$ ranking lowest and meeting both $C1$ and $C2$, the alternative ζ_λ will be declared a CS: $C1$ admissible: If ζ_λ and ζ_μ represent top alternatives in $\mathbb{Q}$, then $\mathbb{Q}(\zeta_\mu) - \mathbb{Q}(\zeta_\lambda) \geq \frac{1}{n-1}$. Here n is the number of parameters.

$C2$ admissible: The alternative ζ_λ is ranked by $[\mathbb{S}_i^l, \mathbb{S}_i^u] = \frac{\mathbb{S}_i^l + \mathbb{S}_i^u}{2}$ and (or) $[\mathbb{R}_i^l, \mathbb{R}_i^u] = \frac{\mathbb{R}_i^l + \mathbb{R}_i^u}{2}$.

If $C1$ and $C2$ are not simultaneously satisfied, then there exist multiple CSs:

(i) If $C1$ is true, then both alternatives ζ_λ and ζ_μ are called the CSs:

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(ii) If $C1$ is false, then the alternatives ζ_λ, ζ_μ,..., ζ_η are called the CSs, where ζ_η is founded by $\mathbb{Q}(\zeta_\eta)-\mathbb{Q}(\zeta_\lambda) \geq \frac{1}{n-1}$.

The top five companies on the stock exchange are being purchased by an investment company in order to invest money in them. The companies invested some of their cash according to the top five ranked companies in 30 dollar, 25 dollar, 20 dollar, 15 dollar and 10 dollar percentages, so minimized the impact of this factor.
Step-1: Suppose $[\Theta^l, \Theta^u] = \left\{[\Theta^l_i, \Theta^u_i] : \right\}$ (i goes to 1 to 5) is a decision makers, $\mathscr{C} = \{\zeta_i : i = 1, 2, ..., 10\}$ is the collection of companies/alternatives and $D = \{e_i : i = 1, 2, ..., 5\}$ is a family of parameters, where $e_1 =$ Momentum, $e_2 =$ Value, $e_3 =$ Growth, $e_4 =$ Volatility, $e_5 =$ Quality.
Step-2: Linguistic variables in tabular form

$Linguistic\ variables$	$V weights$
$Very\ Good\ Estimate(VGE)$	$[0.9, 0.95]$
$Good\ Estimate(GE)$	$[0.8, 0.9]$
$Average\ Estimate(AE)$	$[0.65, 0.8]$
$Poor\ Estimate(PE)$	$[0.5, 0.65]$
$Very\ Poor\ Estimate(VPE)$	$[0.35, 0.5]$

Form the weighted parameter matrix is given as

$$\begin{aligned}\mathcal{P} &= [\varsigma^l_{ij}, \varsigma^u_{ij}]_{5\times 5}\\ &= \begin{bmatrix} GE & AE & VGE & PE & VPE\\ AE & PE & GE & VPE & VGE\\ PE & VGE & VPE & GE & AE\\ VGE & GE & AE & VPE & PE\\ VPE & AE & VGE & AE & GE\end{bmatrix}\\ &= \begin{bmatrix} [0.8, 0.9] & [0.65, 0.8] & [0.9, 0.95] & [0.5, 0.65] & [0.35, 0.5]\\ [0.65, 0.8] & [0.5, 0.65] & [0.8, 0.9] & [0.35, 0.5] & [0.9, 0.95]\\ [0.5, 0.65] & [0.9, 0.95] & [0.35, 0.5] & [0.8, 0.9] & [0.65, 0.8]\\ [0.9, 0.95] & [0.8, 0.9] & [0.65, 0.8] & [0.35, 0.5] & [0.5, 0.65]\\ [0.35, 0.5] & [0.65, 0.8] & [0.9, 0.95] & [0.65, 0.8] & [0.8, 0.9]\end{bmatrix}\end{aligned}$$

where $[\varsigma^l_{ij}, \varsigma^u_{ij}]$ denotes the weight to $[\Theta^l_i, \Theta^u_i]$.
Step-3: As a result, the normalized weighted decision matrix can be formed as follows:

$$\begin{aligned}\widehat{\mathcal{N}} &= \left[\widehat{\eta}^l_{ij}, \widehat{\eta}^u_{ij}\right]_{5\times 5}\\ &= \begin{bmatrix} [0.46, 0.5175] & [0.3517, 0.4329] & [0.4807, 0.5074] & [0.3246, 0.422] & [0.2012, 0.2875]\\ [0.3737, 0.46] & [0.2706, 0.3517] & [0.4273, 0.4807] & [0.2272, 0.3246] & [0.5175, 0.5462]\\ [0.2875, 0.3737] & [0.487, 0.5141] & [0.1869, 0.2671] & [0.5194, 0.5843] & [0.3737, 0.46]\\ [0.5175, 0.5462] & [0.4329, 0.487] & [0.3472, 0.4273] & [0.2272, 0.3246] & [0.2875, 0.3737]\\ [0.2012, 0.2875] & [0.3517, 0.4329] & [0.4807, 0.5074] & [0.422, 0.5194] & [0.46, 0.5175]\end{bmatrix}.\end{aligned}$$

and weighted vector can be written as
$\mathcal{W} = ([0.0968, 0.1366], [0.0924, 0.1268], [0.0938, 0.1217], [0.1027, 0.1641], [0.0968, 0.1366])$.

Step-4: The matrix $\left[\Lambda^l, \Lambda^u\right] = \frac{\left[\Theta^l_1, \Theta^u_1\right] + \left[\Theta^l_2, \Theta^u_2\right] + ... + \left[\Theta^l_5, \Theta^u_5\right]}{5}$

$$= \begin{bmatrix} [0.85, 0.9], [0.65, 0.7], [0.1, 0.15]) & ([0.2, 0.4], [0.7, 0.8], [0.6, 0.8]) & ([0.5, 0.6], [0.55, 0.65], [0.4, 0.5])\\ [0.6, 0.7], [0.75, 0.8], [0.3, 0.4]) & ([0.75, 0.8], [0.8, 0.9], [0.2, 0.25]) & ([0.8, 0.9], [0.4, 0.5], [0.1, 0.2])\\ [0.5, 0.9], [0.85, 0.9], [0.1, 0.5]) & ([0.65, 0.7], [0.7, 0.8], [0.3, 0.35]) & ([0.7, 0.8], [0.45, 0.5], [0.2, 0.3])\\ [0.7, 0.8], [0.3, 0.7], [0.2, 0.3]) & ([0.6, 0.65], [0.5, 0.65], [0.35, 0.4]) & ([0.8, 0.85], [0.65, 0.75], [0.15, 0.2])\\ [0.5, 0.8], [0.4, 0.65], [0.2, 0.5]) & ([0.3, 0.75], [0.4, 0.7], [0.25, 0.7]) & ([0.75, 0.8], [0.65, 0.7], [0.2, 0.25])\\ [0.7, 0.9], [0.8, 0.85], [0.1, 0.3]) & ([0.6, 0.65], [0.4, 0.5], [0.35, 0.4]) & ([0.55, 0.6], [0.6, 0.7], [0.4, 0.45])\\ [0.55, 0.7], [0.7, 0.75], [0.3, 0.45]) & ([0.55, 0.6], [0.5, 0.55], [0.4, 0.45]) & ([0.55, 0.6], [0.45, 0.5], [0.4, 0.45])\\ [0.45, 0.6], [0.65, 0.7], [0.4, 0.55]) & ([0.65, 0.7], [0.55, 0.8], [0.3, 0.35]) & ([0.65, 0.7], [0.65, 0.75], [0.3, 0.35])\\ [0.6, 0.8], [0.75, 0.8], [0.2, 0.4]) & ([0.6, 0.75], [0.65, 0.8], [0.25, 0.4]) & ([0.6, 0.8], [0.5, 0.55], [0.2, 0.4])\\ [0.65, 0.85], [0.5, 0.65], [0.15, 0.35]) & ([0.7, 0.85], [0.6, 0.65], [0.15, 0.3]) & ([0.5, 0.6], [0.35, 0.45], [0.4, 0.5])\\ [0.6, 0.7], [0.7, 0.8], [0.3, 0.4]) & ([0.65, 0.7], [0.6, 0.65], [0.3, 0.35]) & \\ [0.5, 0.65], [0.65, 0.85], [0.35, 0.5]) & ([0.55, 0.6], [0.45, 0.5], [0.4, 0.45]) & \\ [0.4, 0.55], [0.6, 0.7], [0.45, 0.6]) & ([0.3, 0.45], [0.35, 0.4], [0.55, 0.7]) & \\ [0.35, 0.5], [0.5, 0.55], [0.5, 0.65]) & ([0.45, 0.65], [0.45, 0.6], [0.35, 0.55]) & \\ [0.65, 0.7], [0.7, 0.8], [0.3, 0.35]) & ([0.55, 0.6], [0.5, 0.55], [0.4, 0.45]) & \\ [0.4, 0.5], [0.55, 0.65], [0.5, 0.6]) & ([0.35, 0.75], [0.5, 0.65], [0.25, 0.65]) & \\ [0.6, 0.75], [0.65, 0.7], [0.25, 0.4]) & ([0.45, 0.65], [0.6, 0.7], [0.35, 0.55]) & \\ [0.55, 0.6], [0.6, 0.65], [0.4, 0.45]) & ([0.5, 0.6], [0.4, 0.45], [0.4, 0.5]) & \\ [0.45, 0.5], [0.5, 0.55], [0.5, 0.55]) & ([0.4, 0.55], [0.35, 0.4], [0.45, 0.6]) & \\ [0.4, 0.45], [0.8, 0.85], [0.55, 0.6]) & ([0.55, 0.65], [0.25, 0.5], [0.35, 0.45]) & \end{bmatrix}$$

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$= \left[x^l_{jk}, x^u_{jk}\right]_{10\times 5}$

Step-5: The weighted NVS decision matrix $\left[\Psi^l, \Psi^u\right] = \left[m^l_k \times x^l_{jk}, m^u_k \times x^u_{jk}\right]$

$$
= \begin{bmatrix}
([0.0823, 0.1229], [0.0629, 0.0956], [0.0097, 0.0205]) & ([0.0185, 0.0507], [0.0647, 0.1014], [0.0554, 0.1014]) \\
([0.0581, 0.0956], [0.0726, 0.1092], [0.0291, 0.0546]) & ([0.0693, 0.1014], [0.0739, 0.1141], [0.0185, 0.0317]) \\
([0.0484, 0.1229], [0.0823, 0.1229], [0.0097, 0.0683]) & ([0.0601, 0.0887], [0.0647, 0.1014], [0.0277, 0.0444]) \\
([0.0678, 0.1092], [0.0291, 0.0956], [0.0194, 0.041]) & ([0.0554, 0.0824], [0.0462, 0.0824], [0.0323, 0.0507]) \\
([0.0484, 0.1092], [0.0387, 0.0888], [0.0194, 0.0683]) & ([0.0277, 0.0951], [0.037, 0.0887], [0.0231, 0.0887]) \\
([0.0678, 0.1229], [0.0775, 0.1161], [0.0097, 0.041]) & ([0.0554, 0.0824], [0.037, 0.0634], [0.0323, 0.0507]) \\
([0.0533, 0.0956], [0.0678, 0.1024], [0.0291, 0.0614]) & ([0.0508, 0.0761], [0.0462, 0.0697], [0.037, 0.0571]) \\
([0.0436, 0.0819], [0.0629, 0.0956], [0.0387, 0.0751]) & ([0.0601, 0.0887], [0.0508, 0.1014], [0.0277, 0.0444]) \\
([0.0581, 0.1092], [0.0726, 0.1092], [0.0194, 0.0546]) & ([0.0554, 0.0951], [0.0601, 0.1014], [0.0231, 0.0507]) \\
([0.0629, 0.1161], [0.0484, 0.0888], [0.0145, 0.0478]) & ([0.0647, 0.1078], [0.0554, 0.0824], [0.0139, 0.038]) \\
 & \\
([0.0469, 0.073], [0.0516, 0.0791], [0.0375, 0.0608]) & ([0.0616, 0.1149], [0.0719, 0.1313], [0.0308, 0.0657]) \\
([0.075, 0.1095], [0.0375, 0.0608], [0.0094, 0.0243]) & ([0.0514, 0.1067], [0.0668, 0.1395], [0.0359, 0.0821]) \\
([0.0657, 0.0973], [0.0422, 0.0608], [0.0188, 0.0365]) & ([0.0411, 0.0903], [0.0616, 0.1149], [0.0462, 0.0985]) \\
([0.075, 0.1034], [0.061, 0.0912], [0.0141, 0.0243]) & ([0.0359, 0.0821], [0.0514, 0.0903], [0.0514, 0.1067]) \\
([0.0704, 0.0973], [0.061, 0.0852], [0.0188, 0.0304]) & ([0.0668, 0.1149], [0.0719, 0.1313], [0.0308, 0.0575]) \\
([0.0516, 0.073], [0.0563, 0.0852], [0.0375, 0.0547]) & ([0.0411, 0.0821], [0.0565, 0.1067], [0.0514, 0.0985]) \\
([0.0516, 0.073], [0.0422, 0.0608], [0.0375, 0.0547]) & ([0.0616, 0.1231], [0.0668, 0.1149], [0.0257, 0.0657]) \\
([0.061, 0.0852], [0.061, 0.0912], [0.0281, 0.0426]) & ([0.0565, 0.0985], [0.0616, 0.1067], [0.0411, 0.0739]) \\
([0.0563, 0.0973], [0.0469, 0.0669], [0.0188, 0.0487]) & ([0.0462, 0.0821], [0.0514, 0.0903], [0.0514, 0.0903]) \\
([0.0469, 0.073], [0.0328, 0.0547], [0.0375, 0.0608]) & ([0.0411, 0.0739], [0.0822, 0.1395], [0.0565, 0.0985]) \\
([0.0629, 0.0956], [0.0581, 0.0888], [0.0291, 0.0478]) & \\
([0.0533, 0.0819], [0.0436, 0.0683], [0.0387, 0.0614]) & \\
([0.0291, 0.0614], [0.0339, 0.0546], [0.0533, 0.0956]) & \\
([0.0436, 0.0888], [0.0436, 0.0819], [0.0339, 0.0751]) & \\
([0.0533, 0.0819], [0.0484, 0.0751], [0.0387, 0.0614]) & \\
([0.0339, 0.1024], [0.0484, 0.0888], [0.0242, 0.0888]) & \\
([0.0436, 0.0888], [0.0581, 0.0956], [0.0339, 0.0751]) & \\
([0.0484, 0.0819], [0.0387, 0.0614], [0.0387, 0.0683]) & \\
([0.0387, 0.0751], [0.0339, 0.0546], [0.0436, 0.0819]) & \\
([0.0533, 0.0888], [0.0242, 0.0683], [0.0339, 0.0614]) &
\end{bmatrix}
$$

$= \left[\zeta^l_{jk}, \zeta^u_{jk}\right]_{10\times 5}$

Step-6: In the following table, you will be able to find NVS-PIS and NVS-NIS.

$\widehat{\zeta^+}$	$NVS-PIS$
$\widehat{\zeta^+_1}$	$([0.0823, 0.1229], [0.0291, 0.0888], [0.0097, 0.0205])$
$\widehat{\zeta^+_2}$	$([0.0693, 0.1078], [0.037, 0.0634], [0.0139, 0.0317])$
$\widehat{\zeta^+_3}$	$([0.075, 0.1095], [0.0328, 0.0547], [0.0094, 0.0243])$
$\widehat{\zeta^+_4}$	$([0.0668, 0.1231], [0.0514, 0.0903], [0.0257, 0.0575])$
$\widehat{\zeta^+_5}$	$([0.0629, 0.1024], [0.0242, 0.0546], [0.0242, 0.0478])$

$\widehat{\zeta^-}$	$NVS-NIS$
$\widehat{\zeta^-_1}$	$([0.0436, 0.0819], [0.0823, 0.1229], [0.0387, 0.0751])$
$\widehat{\zeta^-_2}$	$([0.0185, 0.0507], [0.0739, 0.1141], [0.0554, 0.1014])$
$\widehat{\zeta^-_3}$	$([0.0469, 0.073], [0.061, 0.0912], [0.0375, 0.0608])$
$\widehat{\zeta^-_4}$	$([0.0359, 0.0739], [0.0822, 0.1395], [0.0565, 0.1067])$
$\widehat{\zeta^-_5}$	$([0.0291, 0.0614], [0.0581, 0.0956], [0.0533, 0.0956])$

Step-7: Taking $\kappa = 0.5$, we found that the values of $[\mathbb{S}^l_i, \mathbb{S}^u_i]$, $[\mathbb{R}^l_i, \mathbb{R}^u_i]$ and $\mathbb{Q}_i$.

$Alternative$	$\left[\mathbb{S}^l_i, \mathbb{S}^u_i\right]$	$\left[\mathbb{R}^l_i, \mathbb{R}^u_i\right]$	$\mathbb{Q}_i$
ζ_1	$[0.3829, 0.5623]$	$[0.0935, 0.1389]$	0.5988
ζ_2	$[0.3413, 0.5112]$	$[0.0921, 0.1533]$	0.3587
ζ_3	$[0.4075, 0.5312]$	$[0.1028, 0.1407]$	0.6958
ζ_4	$[0.3974, 0.4965]$	$[0.1122, 0.1248]$	0.5644
ζ_5	$[0.3915, 0.5252]$	$[0.1064, 0.1349]$	0.6278
ζ_6	$[0.4129, 0.5409]$	$[0.1043, 0.1345]$	0.7272
ζ_7	$[0.4002, 0.5024]$	$[0.0886, 0.1285]$	0.3627
ζ_8	$[0.3843, 0.4884]$	$[0.1013, 0.1114]$	0.3037
ζ_9	$[0.4005, 0.4822]$	$[0.1014, 0.1143]$	0.3583
ζ_{10}	$[0.4066, 0.4923]$	$[0.0987, 0.1568]$	0.6165

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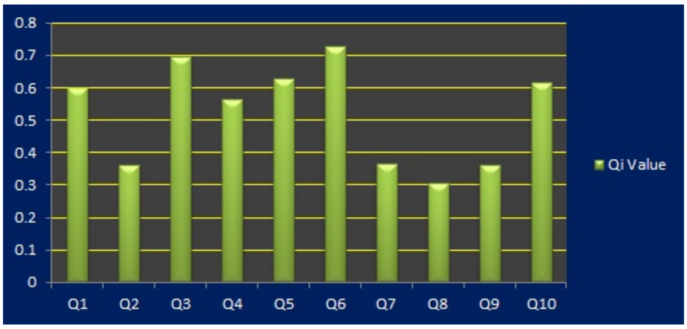

Figure 1 Graphical representation using MCGDM based on VIKOR.

Step-8: The ranking of alternatives $\mathbb{Q}_i$ are $\zeta_8 \leq \zeta_9 \leq \zeta_2 \leq \zeta_7 \leq \zeta_4 \leq \zeta_1 \leq \zeta_{10} \leq \zeta_5 \leq \zeta_3 \leq \zeta_6$.
Now, $\mathbb{Q}(\zeta_9) - \mathbb{Q}(\zeta_8) = 0.0546 \ngeq \frac{1}{4}$. Thus, the condition $C1$ is false, further $\mathbb{Q}(\zeta_4) - \mathbb{Q}(\zeta_8) = 0.2607 \geq \frac{1}{4}$. Therefore, we decide $\zeta_8, \zeta_9, \zeta_2, \zeta_7$ and ζ_4 are multiple CSs. It is therefore imperative that the firm invests in the future 30% on ζ_8, 25% on ζ_9, 20% on ζ_2, 15% on ζ_7 and 10% on ζ_4.

4 Conclusion:

In this communication, a new concept for making decisions under uncertainty has been developed called NVS set. VIKOR methods can be used for MCDM in groups in a few ways. This is an extension of the vague soft set and the neutosophic soft set. By using AOs that are based on NVS linguistic VIKOR algorithms, this algorithm implements linguistic VIKOR approaches. On the basis of interactions with the NVS aggregation operator, we were able to determine the scores function values. For each alternative, utility $\mathbb{S}$ values, regret $\mathbb{R}$ values, and compromise $\mathbb{Q}$ values differed based on the VIKOR approach. Our compromise solution was derived based on the ranking of choices using VIKOR. Additionally, we have included different types of statistical charts as well as graphs to illustrate the ranking of alternatives that we are considering.

Conflicts of Interest: The authors declare no conflict of interest.

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