

Research Article

An Improved EDAS Method Based on Bipolar Neutrosophic Set and Its Application in Group Decision-Making

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The bipolar neutrosophic set is a suitable instrument to tackle the information with vagueness, complexity, and uncertainty. In this study, we improved the original EDAS (the evaluation based on distance from average solution) with bipolar neutrosophic numbers (BNNs) for a multiple-criteria group decision-making (MCGDM) problem. We calculated the average solution under all the criteria by two existing aggregation operators of BNNs. Then, we computed the positive distance and the negative distance from each alternative to the average ideal solution and determined the appraisal score of alternatives. Based on these scores, we obtained the ranking result. Finally, we demonstrated the practicability, stability, and capability of the improved EDAS method by analyzing the influence parameters and comparing results with an extended VIKOR method.

1. Introduction

Zadeh first defined the theory of fuzzy set (FS) [1] to represent the uncertain information through the membership function. However, there are some situations in which the membership function finds it hard to depict its complete information. So, Pawlak anticipated it by introducing the theory of rough set (RS) [2] as a mathematical model for processing and expressing incomplete information in data sciences with the upper approximation value and the lower approximation value of a set. Molodtsov then described the concept of soft set (SS) [3] to avoid the difficulties of using an adequate parametrization. Later on, Lee extended the FS by introducing bipolar valued fuzzy sets [4] whose range of membership degree is augmented from the previous interval from 0 to 1 to the new one from -1 to 1.

However, the three abovementioned theories cannot differentiate between ignoring and uncertain information that are extensively obtainable in the actual case. For

instance, assume that there exist eleven decision makers (DMs), of which 3 DMs agree, 2 DMs disagree, 4 DMs are uncertain, and 2 DMs give up. For this case, those theories cannot precisely express. To tackle this condition, Smarandache [5] first inducted the concept of a neutrosophic set (NS) by accepting a truth-membership function degree, an indeterminacy-membership degree, and a falsity-membership function degree. For the above condition, the NS can express the information by $\{x, (0.3, 0.2, 0.4)\}$. Due to its difficulty to be applied in practical problems such as in science and engineering, Wang et al. [6] improved the NS to be more convenient by proposing single-valued neutrosophic sets (SVNSs). Sunderraman and Wang [7] also contributed to studying interval neutrosophic sets (INSSs). Ye [8] conferred a new idea of simplified neutrosophic sets (SNSs) for MCDM problems. Wang and Li [9] provided an idea of multivalued neutrosophic sets (MVNSs) and attempted to implement MCDM with the TODIM method. Moreover, Peng et al. [10] also explored the approach of MVNSs with qualitative flexibility based on likelihood.

Additionally, many people tend to consider positive and negative effects [11] or bipolarity in decision-making. Positive information describes things that are possible, adequate, authorized, wanted, or acceptable. Meanwhile, negative statements state things that are impossible, insufficient, unpermitted, undesired, or rejected. Hence, from this idea and the adoption of bipolar FS [3, 12], Deli et al., in [13], introduced bipolar neutrosophic sets (BNSs). They also addressed some characteristics, theorems, and aggregation operators of the BNS and executed them in an example of buying a car. Later on, the BNS becomes an exciting topic in the theory of neutrosophic. Deli and Subas [14] depicted correlation coefficient similarity for handling MCDM problems with BNS. Similarly, Sahin et al. [15] addressed similarity measures for MCDM using BNSs by proposing the Jaccard vector. Wang et al. [16] introduced Frank operations of BNSs and defined Frank bipolar neutrosophic Choquet Bonferroni mean operators. Fahmi and Amin [17] constructed bipolar neutrosophic fuzzy (BNF) operators and applied them to develop a MCDM technique. Zhao et al. [18] developed an integrated TOPSIS method based on the theory of cumulative prospect for solving MCGDM under interval-valued BNSs information.

Many fabulous researchers have also applied the concept of NS using the MCGDM strategy to deal with uncertainties in decision-making problems. Ye [19] extended a decision-making method based on single-valued neutrosophic interval numbers (SVNINs) for MCGDM problems. Wei et al. [20] improved an original COPRAS for single-valued neutrosophic 2-tuple linguistic sets (SVN2TLs) and applied them to deal with MCGDM problems. Zhang et al. [21] developed a new MCGDM strategy for SNSs by combining SNSs with their weighted distance measures.

Nevertheless, integrating the concept of NS with a decision-making method will make a useful instrument for determining a more feasible and acceptable solution in the decision-making process. One of many traditional decision-making methods is an evaluation based on the distance from the average solution (EDAS) method. Compared with other methods such as TOPSIS [22], TODIM [23], AHP [24], VIKOR [25], ELECTRE [26, 27], MABAC [28], and MOORA [29], it has particular eminence in selecting optimal solutions. It utilizes the positive and negative distance from the average solution (AVGS) to determine the optimal solution of alternatives. Additionally, it has some valuable features [30, 31]. First, the calculation results by EDAS are well stable and consistent for given different criteria weights. Second, the mathematical formulas for calculating the results are fewer and simple. Third, it can anticipate negative and zero values in the AVGS, and fourth, it provides opportunities to extend this method with many other strategies. These make the EDAS be a suitable auxiliary to yield acceptable decision-making results.

Many prestigious researchers have studied and explored this method. Ghorabae et al. [32, 33] continued to investigate the EDAS method by integrating the concept of trapezoidal fuzzy numbers to express a linguistic term in a

fuzzy environment. Jana and Pal [34] improved EDAS by utilizing bipolar fuzzy numbers to select the best construction company in a road project tender. Karaşan and Kahraman [35] developed an extended EDAS by fusing intuitionistic fuzzy and type-2 fuzzy versions to prioritize the sustainability of development goals in the United Nation. Ghorabae et al. [36] integrated EDAS with stochastic for tackling problems when the alternative values on each criterion do not form a normal distribution. Yahya et al. [37] extended EDAS with the intuitionistic fuzzy rough Frank to choose a construction company. Li et al. [38] proposed a hybrid operator and applied it in analyzing an MCGDM using the EDAS method. Liang [39] utilized EDAS with the fuzzy concept to evaluate the efficiency of energy projects.

1.1. Research Gap. EDAS based an MCGDM strategy under BNS environment. This manuscript will respond to the two following questions. (1) Is there a possibility to improve EDAS in the BNS environment? (2) Is there a possibility to develop a novel EDAS based on BNS in group decision-making?

1.2. Motivation and Objectives. The abovementioned analysis [5–39] outlines the motivation of this study to propose a novel EDAS approach in the BNS environment for dealing with MCGDM problems. Meanwhile, the objectives of this manuscript are to improve the EDAS approach with BNS and design a new MCGDM based on improved EDAS under the BNS environment.

1.3. Main Contributions. Therefore, we summarize the main contributions of this manuscript as below. Firstly, we improve an EDAS method to tackle an MCGDM problem in which the decision makers (DMs) evaluate the information under the BNS environment. Secondly, we extend some calculation steps of the positive distance and negative distance in the improved EDAS algorithm and allow the DMs to give assessments based on their opinions in computing all alternative evaluations. Thirdly, we developed an enlarged EDAS based on BNS for tackling MCGDM problems. Finally, we demonstrate an illustrative example in this manuscript to prove the practicability, stability, and capability of our proposed EDAS to conquer an MCGDM problem.

The manuscript is neatly written as follows. Section 2 acquaints the basic concepts of NS and BNS and reviews some characteristics, operations, and weighted aggregation operators of BNS. In Section 3, the improved EDAS method with BNS for the MCGDM problem is introduced. In Section 4, the analysis of comparison results using the improved EDAS algorithm and some other approaches are performed through a numerical example of social welfare assistance recipients to illustrate the practicability and effectiveness of the improved EDAS method. Lastly, some valuable conclusions and preferable future works are addressed in Section 5.

2. Basic Concepts and Definitions

This section brings back some theoretical concepts of an NS and a BNS and some aggregation operators of the BNS.

2.1. Neutrosophic Set

Definition 1 (see [5]). Let S be a universal set with a general element in S denoted by s ; then, a neutrosophic set (NS) X in S is characterized by a truth-membership function $T_X(s): S \rightarrow [0^-, 1^+]$, an indeterminacy-membership function $I_X(s): S \rightarrow [0^-, 1^+]$, and a falsity-membership function $F_X(s): S \rightarrow [0^-, 1^+]$. Neutrosophic set X can be expressed as

$$X = \{s, \langle T_X(s), I_X(s), F_X(s) \rangle : s \in S\}, \quad (1)$$

where $T_X(s), I_X(s), F_X(s) \in [0^-, 1^+]$, and $0^- \leq T_X(s) + I_X(s) + F_X(s) \leq 3^+$.

Later on, Wang et al. [6] put forward the theory of SVNNS so that it can be easy to apply it in real applications of science and engineering.

Definition 2 (see [6]). Let S be a universal set with a general element s in S ; then, a single-valued neutrosophic set (SVNS) Y in S is characterized by a truth-membership function $T_Y(s): S \rightarrow [0, 1]$, an indeterminacy-membership function $I_Y(s): S \rightarrow [0, 1]$, and a falsity-membership function $F_Y(s): S \rightarrow [0, 1]$. The single-valued neutrosophic set Y can be defined as

$$Y = \{s, \langle T_Y(s), I_Y(s), F_Y(s) \rangle : s \in S\}, \quad (2)$$

where $T_Y(s), I_Y(s), F_Y(s) \in [0, 1]$ and $0 \leq T_Y(s) + I_Y(s) + F_Y(s) \leq 3$.

2.2. Bipolar Neutrosophic Set

Definition 3 (see [13]). Let S be a universal set with a general element in S denoted by s ; then, a bipolar neutrosophic set B in S is characterized by the positive-membership degree $T_B^+(s), I_B^+(s), F_B^+(s)$, where $T_B^+(s): S \rightarrow [0, 1]$ is a truth-membership function, $I_B^+(s): S \rightarrow [0, 1]$ is an indeterminacy-membership function, and $F_B^+(s): S \rightarrow [0, 1]$ is a falsity-membership function, and the negative-membership degree, where $T_B^-(s): S \rightarrow [-1, 0]$ is a truth-membership function, $I_B^-(s): S \rightarrow [-1, 0]$ is an indeterminacy-membership function, and $F_B^-(s): S \rightarrow [-1, 0]$ is a falsity-membership function. The bipolar neutrosophic set B can be expressed as an object of the form:

$$B = \{s, \langle T_B^+(s), I_B^+(s), F_B^+(s), T_B^-(s), I_B^-(s), F_B^-(s) \rangle : s \in S\}, \quad (3)$$

where $T_B^+(s), I_B^+(s), F_B^+(s) \in [0, 1]$ and $T_B^-(s), I_B^-(s), F_B^-(s) \in [-1, 0]$.

Definition 4 (see [13]). Let $B_1 = \langle T_{B_1}^+(s), I_{B_1}^+(s), F_{B_1}^+(s), T_{B_1}^-(s), I_{B_1}^-(s), F_{B_1}^-(s) \rangle$ and $B_2 = \langle T_{B_2}^+(s), I_{B_2}^+(s), F_{B_2}^+(s), T_{B_2}^-(s), I_{B_2}^-(s), F_{B_2}^-(s) \rangle$ be two BNSs; then, the following conditions are satisfied:

(1) $(B_1 \cup B_2)(s) = \left\langle \begin{array}{l} \max(T_{B_1}^+(s), T_{B_2}^+(s)), ((I_{B_1}^+(s) + I_{B_2}^+(s))/2), \\ \min(F_{B_1}^+(s), F_{B_2}^+(s)), \\ \min(T_{B_1}^-(s), T_{B_2}^-(s)), ((I_{B_1}^-(s) + I_{B_2}^-(s))/2), \\ \max(F_{B_1}^-(s), F_{B_2}^-(s)) \end{array} \right\rangle$

$$(2) (B_1 \cap B_2)(s) = \left\langle \begin{array}{l} \min(T_{B_1}^+(s), T_{B_2}^+(s)), ((I_{B_1}^+(s) + I_{B_2}^+(s))/2), \\ \max(F_{B_1}^+(s), F_{B_2}^+(s)), \\ \max(T_{B_1}^-(s), T_{B_2}^-(s)), ((I_{B_1}^-(s) + I_{B_2}^-(s))/2), \\ \min(F_{B_1}^-(s), F_{B_2}^-(s)) \end{array} \right\rangle$$

$$(3) B_1^C(s) = \left\langle \begin{array}{l} 1 - T_{B_1}^+(s), 1 - I_{B_1}^+(s), 1 - F_{B_1}^+(s), \\ -1 - T_{B_1}^-(s), -1 - I_{B_1}^-(s), -1 - F_{B_1}^-(s) \end{array} \right\rangle$$

where $B_1^C(s)$ is the complement of $B_1(s)$, for all $s \in S$

For more convenience, a bipolar neutrosophic number (BNN) is denoted as $\mathcal{B} = \langle T_{\mathcal{B}}^+, I_{\mathcal{B}}^+, F_{\mathcal{B}}^+, T_{\mathcal{B}}^-, I_{\mathcal{B}}^-, F_{\mathcal{B}}^- \rangle$.

Definition 5 (see [13]). Let $\mathcal{B}_1 = \langle T_{\mathcal{B}_1}^+(s), I_{\mathcal{B}_1}^+(s), F_{\mathcal{B}_1}^+(s), T_{\mathcal{B}_1}^-(s), I_{\mathcal{B}_1}^-(s), F_{\mathcal{B}_1}^-(s) \rangle$ and $\mathcal{B}_2 = \langle T_{\mathcal{B}_2}^+(s), I_{\mathcal{B}_2}^+(s), F_{\mathcal{B}_2}^+(s), T_{\mathcal{B}_2}^-(s), I_{\mathcal{B}_2}^-(s), F_{\mathcal{B}_2}^-(s) \rangle$ be two bipolar neutrosophic numbers (BNNs); then, the following operators of BNNs are depicted as below:

$$(1) \mathcal{B}_1 + \mathcal{B}_2 = \left\langle \begin{array}{l} T_{\mathcal{B}_1}^+ + T_{\mathcal{B}_2}^+ - T_{\mathcal{B}_1}^+ T_{\mathcal{B}_2}^+, I_{\mathcal{B}_1}^+ I_{\mathcal{B}_2}^+, F_{\mathcal{B}_1}^+ F_{\mathcal{B}_2}^+, \\ -(T_{\mathcal{B}_1}^- T_{\mathcal{B}_2}^-), -(I_{\mathcal{B}_1}^- I_{\mathcal{B}_2}^-), -(F_{\mathcal{B}_1}^- F_{\mathcal{B}_2}^-), -(F_{\mathcal{B}_1}^- F_{\mathcal{B}_2}^-) \end{array} \right\rangle$$

$$(2) \mathcal{B}_1 \cdot \mathcal{B}_2 = \left\langle \begin{array}{l} T_{\mathcal{B}_1}^+ T_{\mathcal{B}_2}^+, I_{\mathcal{B}_1}^+ + I_{\mathcal{B}_2}^+ - I_{\mathcal{B}_1}^+ I_{\mathcal{B}_2}^+, F_{\mathcal{B}_1}^+ + F_{\mathcal{B}_2}^+ - F_{\mathcal{B}_1}^+ F_{\mathcal{B}_2}^+, \\ -(-T_{\mathcal{B}_1}^- - T_{\mathcal{B}_2}^- - T_{\mathcal{B}_1}^- T_{\mathcal{B}_2}^-), -(I_{\mathcal{B}_1}^- I_{\mathcal{B}_2}^-), -(F_{\mathcal{B}_1}^- F_{\mathcal{B}_2}^-) \end{array} \right\rangle$$

$$(3) \chi^{\mathcal{B}_1} = \left\langle \begin{array}{l} 1 - (1 - T_{\mathcal{B}_1}^+)^{\chi}, (I_{\mathcal{B}_1}^+)^{\chi}, (F_{\mathcal{B}_1}^+)^{\chi}, \\ -(-T_{\mathcal{B}_1}^-)^{\chi}, -(I_{\mathcal{B}_1}^-)^{\chi}, -(1 - (1 - F_{\mathcal{B}_1}^-)^{\chi}) \end{array} \right\rangle$$

$$(4) (\mathcal{B}_1)^{\chi} = \left\langle \begin{array}{l} (T_{\mathcal{B}_1}^+)^{\chi}, 1 - (1 - I_{\mathcal{B}_1}^+)^{\chi}, 1 - (1 - F_{\mathcal{B}_1}^+)^{\chi}, \\ -(1 - (1 - (-T_{\mathcal{B}_1}^-)^{\chi})), -(I_{\mathcal{B}_1}^-)^{\chi}, -(F_{\mathcal{B}_1}^-)^{\chi} \end{array} \right\rangle \quad \text{where } \chi > 0.$$

Definition 6 (see [13]). Let $\mathcal{B}_a = \langle T_{\mathcal{B}_a}^+(s), I_{\mathcal{B}_a}^+(s), F_{\mathcal{B}_a}^+(s), T_{\mathcal{B}_a}^-(s), I_{\mathcal{B}_a}^-(s), F_{\mathcal{B}_a}^-(s) \rangle$ be a BNN; then, the functions of score $\mathcal{S}(\mathcal{B}_a)$, accuracy $\mathcal{A}(\mathcal{B}_a)$, and certainty $\mathcal{C}(\mathcal{B}_a)$ can be calculated as follows:

$$(1) \mathcal{S}(\mathcal{B}_a) = (T_{\mathcal{B}_a}^+ + 1 - I_{\mathcal{B}_a}^+ + 1 - F_{\mathcal{B}_a}^+ + 1 + T_{\mathcal{B}_a}^- - I_{\mathcal{B}_a}^- - F_{\mathcal{B}_a}^-)/6$$

$$(2) \mathcal{A}(\mathcal{B}_a) = T_{\mathcal{B}_a}^+ - F_{\mathcal{B}_a}^+ + T_{\mathcal{B}_a}^- - F_{\mathcal{B}_a}^-$$

$$(3) \mathcal{C}(\mathcal{B}_a) = T_{\mathcal{B}_a}^+ - F_{\mathcal{B}_a}^-.$$

Definition 7 (see [13]). Let $\mathcal{B}_a = \langle T_{\mathcal{B}_a}^+(s), I_{\mathcal{B}_a}^+(s), F_{\mathcal{B}_a}^+(s), T_{\mathcal{B}_a}^-(s), I_{\mathcal{B}_a}^-(s), F_{\mathcal{B}_a}^-(s) \rangle$ and $\mathcal{B}_b = \langle T_{\mathcal{B}_b}^+(s), I_{\mathcal{B}_b}^+(s), F_{\mathcal{B}_b}^+(s), T_{\mathcal{B}_b}^-(s), I_{\mathcal{B}_b}^-(s), F_{\mathcal{B}_b}^-(s) \rangle$ be two BNNs; then, the relation methods of the three BNN functions are the following:

- (1) If $\mathcal{S}(\mathcal{B}_b) > \mathcal{S}(\mathcal{B}_a)$, then \mathcal{B}_b is greater than \mathcal{B}_a , that is, \mathcal{B}_b is superior to \mathcal{B}_a , notated by $\mathcal{B}_b > \mathcal{B}_a$
- (2) If $\mathcal{S}(\mathcal{B}_b) = \mathcal{S}(\mathcal{B}_a)$ and $\mathcal{A}(\mathcal{B}_b) > \mathcal{A}(\mathcal{B}_a)$, then \mathcal{B}_b is greater than \mathcal{B}_a , that is, \mathcal{B}_b is superior to \mathcal{B}_a , notated by $\mathcal{B}_b < \mathcal{B}_a$
- (3) If $\mathcal{S}(\mathcal{B}_b) = \mathcal{S}(\mathcal{B}_a)$, $\mathcal{A}(\mathcal{B}_b) = \mathcal{A}(\mathcal{B}_a)$, and $\mathcal{C}(\mathcal{B}_b) = \mathcal{C}(\mathcal{B}_a)$, then \mathcal{B}_b is greater than \mathcal{B}_a , that is, \mathcal{B}_b is superior to \mathcal{B}_a , notated by $\mathcal{B}_b > \mathcal{B}_a$

- (4) If $\mathcal{S}(\mathcal{C}_b) = \mathcal{S}(\mathcal{C}_a)$, $\mathcal{A}(\mathcal{C}_b) = \mathcal{A}(\mathcal{C}_a)$, and $\mathcal{C}(\mathcal{C}_b) = \mathcal{C}(\mathcal{C}_a)$, then \mathcal{C}_b is equal to \mathcal{C}_a , that is, \mathcal{C}_b is indifferent to \mathcal{C}_a , notated by $\mathcal{C}_b = \mathcal{C}_a$

In decision-making conditions, benefit-type criterion and cost-type criterion will sure exist concurrently. Based on

[40], we adjust a normalization procedure of a BNN for benefit-type (C_{benefit}) and cost-type (C_{Cost}) criterion.

Definition 8. Let $\mathcal{C}_a = \langle T_{\mathcal{C}_a}^+(s), I_{\mathcal{C}_a}^+(s), F_{\mathcal{C}_a}^+(s), T_{\mathcal{C}_a}^-(s), I_{\mathcal{C}_a}^-(s), F_{\mathcal{C}_a}^-(s) \rangle$ be a BNN; then, the normalized BNN is expressed as

$$\hat{\mathcal{C}}_a = \begin{cases} \left\langle \begin{matrix} T_{\mathcal{C}_a}^+(s), I_{\mathcal{C}_a}^+(s), F_{\mathcal{C}_a}^+(s), \\ T_{\mathcal{C}_a}^-(s), I_{\mathcal{C}_a}^-(s), F_{\mathcal{C}_a}^-(s) \end{matrix} \right\rangle, & \text{for } C_{\text{benefit}}, \\ \left\langle \begin{matrix} 1 - T_{\mathcal{C}_a}^+(s), 1 - I_{\mathcal{C}_a}^+(s), 1 - F_{\mathcal{C}_a}^+(s), \\ -1 - T_{\mathcal{C}_a}^-(s), -1 - I_{\mathcal{C}_a}^-(s), -1 - F_{\mathcal{C}_a}^-(s) \end{matrix} \right\rangle, & \text{for } C_{\text{Cost}}. \end{cases} \quad (4)$$

2.3. Some Weighted Aggregation Operators of BNNs

Definition 9 (see [13]). Let $\tilde{\mathcal{B}} = \{\mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3, \dots, \mathcal{C}_n\}$ be the set of n BNNs and $\mathcal{W} = \{w_1, w_2, \dots, w_n\}$ be the set of

corresponding weights of n BNNs, where $0 \leq w_k \leq 1$ and $\sum_{k=1}^n w_k = 1$. Then, the bipolar neutrosophic number weighted average (BNNWA) operator is expressed as

$$\begin{aligned} \text{BNNWA}_{\mathcal{W}}(\tilde{\mathcal{B}}) &= \sum_{k=1}^n w_k \mathcal{C}_k \\ &= \left\langle \begin{matrix} 1 - \prod_{k=1}^n (1 - T_{\mathcal{C}_k}^+)^{w_k}, \prod_{k=1}^n I_{\mathcal{C}_k}^{+w_k}, \prod_{k=1}^n F_{\mathcal{C}_k}^{+w_k}, \\ -\prod_{k=1}^n (-T_{\mathcal{C}_k}^-)^{w_k}, -\left(1 - \prod_{k=1}^n (1 - (-I_{\mathcal{C}_k}^-))^{w_k}\right), -\left(1 - \prod_{k=1}^n (1 - (-F_{\mathcal{C}_k}^-))^{w_k}\right) \end{matrix} \right\rangle. \end{aligned} \quad (5)$$

Definition 10 (see [13]). Let $\tilde{\mathcal{B}} = \{\mathcal{C}_1, \mathcal{C}_2, \mathcal{C}_3, \dots, \mathcal{C}_n\}$ be the set of n BNNs and $\mathcal{W} = \{w_1, w_2, \dots, w_n\}$ be the set of corresponding weights of n BNNs, where $0 \leq w_k \leq 1$ and

$\sum_{k=1}^n w_k = 1$. Then, the bipolar neutrosophic number weighted geometric (BNNWG) operator is expressed as

$$\begin{aligned} \text{BNNWG}_{\mathcal{W}}(\tilde{\mathcal{B}}) &= \prod_{k=1}^n \mathcal{C}_k^{w_k} \\ &= \left\langle \begin{matrix} \prod_{k=1}^n T_{\mathcal{C}_k}^{+w_k}, 1 - \prod_{k=1}^n (1 - I_{\mathcal{C}_k}^+)^{w_k}, 1 - \prod_{k=1}^n (1 - F_{\mathcal{C}_k}^+)^{w_k}, \\ -\left(1 - \prod_{k=1}^n (1 - (-T_{\mathcal{C}_k}^-))^{w_k}\right), -\prod_{k=1}^n (-I_{\mathcal{C}_k}^-)^{w_k}, -\prod_{k=1}^n (-F_{\mathcal{C}_k}^-)^{w_k} \end{matrix} \right\rangle. \end{aligned} \quad (6)$$

3. The Improved EDAS Method with BNNs

This section depicts an MCGDM methodology by integrating the original EDAS with BNNs. Suppose there is a commission of e decision-makers $\{\text{DM}_1, \text{DM}_2, \dots, \text{DM}_e\}$ with the weight matrix of decision makers $v = \{v_1, v_2, v_3, \dots, v_e\}$ that satisfies $v_k \in [0, 1]$ and $\sum_{k=1}^e v_k = 1$. This is responsible for assessing p alternatives $\{U_1, U_2, \dots, U_p\}$ with q criteria $\{C_1, C_2, \dots, C_q\}$, where the weight matrix of criterion is $\mathcal{W} = \{w_1, w_2, \dots, w_q\}$ that satisfies $w_j \in [0, 1]$ and $\sum_{j=1}^q w_j = 1$. The algorithm of the

improved EDAS method is constructed as below and showed in Figure 1.

3.1. Algorithm

Step 1: establish the evaluated linguistic matrix of decision maker DM_k and transform it as $\mathcal{M}_k = [m_{ij}^k]_{p \times q}$, $i = 1, 2, 3, \dots, p$ and $j = 1, 2, 3, \dots, q$, where $m_{ij}^k = \langle T_{ij}^{+k}, I_{ij}^{+k}, F_{ij}^{+k}, T_{ij}^{-k}, I_{ij}^{-k}, F_{ij}^{-k} \rangle$ is a BNN and represents the bipolar neutrosophic information of

alternative U_i corresponding to criterion C_j by decision maker DM_k .

Step 2: normalize the evaluated BNN matrix $\mathcal{M}_k = [m_{ij}^k]_{p \times q}$ into $\widehat{\mathcal{M}}_k = [\widehat{m}_{ij}^k]_{p \times q}$, where $\widehat{m}_{ij}^k = m_{ij}^k$ for benefit criterion C_j or $\widehat{m}_{ij}^k = \langle 1 - T_{ij}^{+k}, 1 - I_{ij}^{+k}, 1 - F_{ij}^{+k}, 1 - T_{ij}^{-k}, 1 - I_{ij}^{-k}, 1 - F_{ij}^{-k} \rangle$ for cost criterion C_j .

Step 3: based on the normalized BNN decision-making matrix $\widehat{\mathcal{M}}_k = [\widehat{m}_{ij}^k]_{p \times q}$ and the weight matrix of decision makers $v = \{v_1, v_2, v_3, \dots, v_e\}$, we will determine overall \widehat{m}_{ij}^k into a_{ij} by using equation (7) for the BNNWA operator or equation (8) for BNNWG operator. Thus, the aggregated decision-making matrix $\mathcal{A}_k = [a_{ij}]_{p \times q}$, where $a_{ij} = \langle T_{ij}^+, I_{ij}^+, F_{ij}^+, T_{ij}^-, I_{ij}^-, F_{ij}^- \rangle$ is also a BNN:

$$a_{ij} = \left\langle 1 - \prod_{k=1}^e (1 - T_{ij}^{+k})^{v_k}, \prod_{k=1}^e (I_{ij}^{+k})^{v_k}, \prod_{k=1}^e (F_{ij}^{+k})^{v_k}, \right. \\ \left. - \prod_{k=1}^e (-T_{ij}^{-k})^{v_k}, - \left(1 - \prod_{k=1}^e (1 - (-I_{ij}^{-k}))^{v_k} \right), - \left(1 - \prod_{k=1}^e (1 - (-F_{ij}^{-k}))^{v_k} \right) \right\rangle, \quad \text{for BNNWA operator}, \quad (7)$$

$$a_{ij} = \left\langle \prod_{k=1}^e (T_{ij}^{+k})^{v_k}, 1 - \prod_{k=1}^e (1 - I_{ij}^{+k})^{v_k}, 1 - \prod_{k=1}^e (1 - F_{ij}^{+k})^{v_k}, \right. \\ \left. - \left(1 - \prod_{k=1}^e (1 - (-T_{ij}^{-k}))^{v_k} \right), - \prod_{k=1}^e (-I_{ij}^{-k})^{v_k}, - \prod_{k=1}^e (-F_{ij}^{-k})^{v_k} \right\rangle, \quad \text{for BNNWG operator}. \quad (8)$$

Step 4: enumerate the values of the average solution $AV = [\widetilde{a}_{ij}]_{1 \times q}$, where $\widetilde{a}_{ij} = (1/p) \oplus_{i=1}^p a_{ij}$. According to Definition 5, we will obtain as

$$\bigoplus_{i=1}^p a_{ij} = \left\langle 1 - \prod_{i=1}^p (1 - T_{ij}^{+i})^{1/p}, \prod_{i=1}^p (I_{ij}^{+i})^{1/p}, \prod_{i=1}^p (F_{ij}^{+i})^{1/p}, \right. \\ \left. - \prod_{i=1}^p (-T_{ij}^{-i})^{1/p}, - \left(1 - \prod_{i=1}^p (1 - (-I_{ij}^{-i}))^{1/p} \right), - \left(1 - \prod_{i=1}^p (1 - (-F_{ij}^{-i}))^{1/p} \right) \right\rangle. \quad (9)$$

Step 5: calculate the positive and negative distance from average solution PDA = $[p_{ij}]_{p \times q}$ and NDA = $[n_{ij}]_{p \times q}$ by using equation (10), respectively:

$$p_{ij} = \frac{\max\{0, S(a_{ij}) - S(\widetilde{a}_{ij})\}}{S(\widetilde{a}_{ij})}, \quad (10) \\ n_{ij} = \frac{\max\{0, S(\widetilde{a}_{ij}) - S(a_{ij})\}}{S(\widetilde{a}_{ij})}.$$

Step 6: determine the values of the weighted sums of PDA and NDA that notated as $\mathcal{WP} = [p_i]_{p \times 1}$ and $\mathcal{WN} = [n_i]_{p \times 1}$ using

$$p_i = \sum_{j=1}^q w_j p_{ij}, \quad (11) \\ n_i = \sum_{j=1}^q w_j n_{ij}.$$

Step 7: normalize the values p_i and n_i to get $\mathcal{WP}' = [p'_i]_{p \times 1}$ and $\mathcal{WN}' = [n'_i]_{p \times 1}$ using

$$p'_i = \frac{p_i}{\max_{1 \leq i \leq p} \{p_i\}}, \quad (12) \\ n'_i = \frac{n_i}{\max_{1 \leq i \leq p} \{n_i\}}.$$

Step 8: compute the appraisal score of $\mathcal{AS} = [a_i]_{p \times 1}$ for each alternative by using

$$a_i = \varphi (p'_i) + (1 - \varphi) (1 - n'_i), \quad (13)$$

where the DMs can customize the value of φ based on their judgment for positive and negative distances. Especially, when the DM's judgment is neutral and gives $\varphi = 0.5$, equation (13) can be simplified to

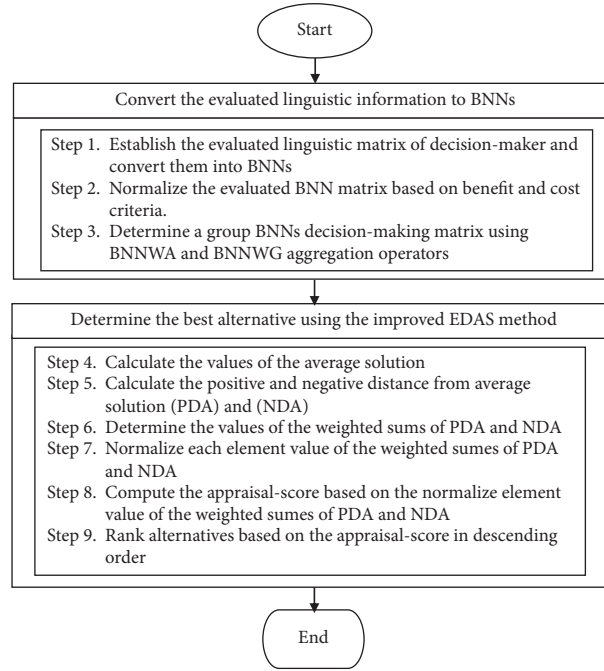


FIGURE 1: The flowchart of the improved EDAS method.

$$as_i = \frac{1}{2} (sp'_i + (1 - sn'_i)). \quad (14)$$

Step 9: create a list of alternatives ranking taking from the sorted values of as_i . The highest value of as_i is the best or the selected alternative.

4. Numerical Example

4.1. An Example for BNNs MCGDM Problem. In this section, we show a case study to distribute poor business groups in distributing a Productive Economic Endeavours (PEE) Program. The Ministry of Social Affairs of the Republic of Indonesia provides this program to aid the micro, small, and medium enterprises (MSMEs). The program aims to enhance the income of these business groups through productive economic endeavours and build social relationships harmony among residents.

Assume the Ministry of Social Affairs wants to select small and medium joint business groups to give them venture capital assistance. The Minister of Social Affairs appointed a committee of the PEE program consisting of three decision makers $\{DM_1, DM_2, DM_3\}$ to assess five potential small and medium joint business groups $\{U_1, U_2, U_3, U_4, U_5\}$. Due to the three decision makers (DMs) have different assessment skills, the minister provided assessment weight to them $v = \{0.37, 0.33, 0.3\}$, respectively.

Afterward, all decision makers decided on four criteria which are the eligibility of business (C_1), quality of management team (C_2), income households (C_3), and business plan (C_4) as requirements in this selection program. Besides, they agreed to give a criteria weight $\mathcal{W} = \{0.25, 0.2, 0.4, 0.15\}$, determine the criteria C_1 , C_2 , and C_4 as a benefit-type criterion, and C_3 as a cost-type criterion.

They used the linguistic variables set $S = \{EL, VL, ML, L, NE, E, MH, VH, EH\}$ to evaluate all alternatives over the cross criteria with their BNN values of the linguistic values, as presented in Table 1.

Tables 2–4 show evaluated values of the three DMs with BNNs for the five alternatives and the four criteria.

To obtain a list of venture capital assistance recipients, we apply the improved EDAS method to evaluate the five joint business groups. The technical calculation steps of the improved EDAS method are as follows:

Step 1: after building the linguistic values matrices of decision makers, we transform them into the BNN decision-making matrices.

Step 2: normalize the BNN decision-making matrices based on the benefit-type and cost-type criteria. We receive the normalized BNN matrices, as shown in Table 5.

Step 3: aggregate the normalized BNN matrices. Based on the given decision makers' weight matrix $v = \{0.37, 0.33, 0.3\}$, we will get the aggregated BNN matrix, as presented in Table 6, using BNNWA operator or Table 7, using BNNWG operator.

Step 4: calculate the values of the average solution using equation (9), and obtain the average solution matrix, as provided in Table 8.

Step 5: by utilizing the average solution matrix and the aggregated BNN matrix (in this step, we use BNNWA operator) and the score function values of alternatives, as shown in Table 9, we calculate all elements of the matrix of PDA and NDA, and the results are provided in Table 10.

Step 6: determine the weighted matrix of PDA which is the multiplication of the matrix of PDA and the matrix of criteria weight \mathcal{W} . Similarly, we perform to the weighted matrix of NDA. According to $\mathcal{W} = \{0.25, 0.2, 0.4, 0.15\}$ and equation (11), we obtain

$$\begin{aligned}\mathcal{W}\mathcal{P} &= \begin{pmatrix} \wp p_1 = 0.0039 \\ \wp p_2 = 0.0842 \\ \wp p_3 = 0.0781 \\ \wp p_4 = 0.0586 \\ \wp p_5 = 0 \end{pmatrix}, \\ \mathcal{W}\mathcal{N} &= \begin{pmatrix} \wp n_1 = 0.219 \\ \wp n_2 = 0.1181 \\ \wp n_3 = 0.0433 \\ \wp n_4 = 0.2059 \\ \wp n_5 = 0.3406 \end{pmatrix}.\end{aligned}\quad (15)$$

Step 7: after normalizing the values of $\wp p_i$ and $\wp n_i$ using equation (12), we then obtain the values of $\wp p'_i$ and $\wp n'_i$:

$$\begin{aligned}\mathcal{W}\mathcal{P}' &= \begin{pmatrix} \wp p'_1 = 0.0464 \\ \wp p'_2 = 1 \\ \wp p'_3 = 0.9277 \\ \wp p'_4 = 0.6996 \\ \wp p'_5 = 0 \end{pmatrix}, \\ \mathcal{W}\mathcal{N}' &= \begin{pmatrix} \wp n'_1 = 0.6432 \\ \wp n'_3 = 0.3468 \\ \wp n'_3 = 0.1272 \\ \wp n'_4 = 0.6046 \\ \wp n'_5 = 1 \end{pmatrix}.\end{aligned}\quad (16)$$

Step 8: when $\varphi = 0.5$ is given in equation (13), the appraisal score $\alpha \wp_i$ ($i = 1, 2, 3, 4, 5$) can be obtained as below. The $\alpha \wp_i$ value is a final value for the alternative U_i :

$$\mathcal{AS} = \begin{pmatrix} \alpha \wp_1 = 0.2016 \\ \alpha \wp_2 = 0.8266 \\ \alpha \wp_3 = 0.9003 \\ \alpha \wp_4 = 0.5475 \\ \alpha \wp_5 = 0 \end{pmatrix}.\quad (17)$$

Step 9: according to the matrix value of AS, the result of alternatives ranking is $U_3 > U_2 > U_4 > U_1 > U_5$. Obviously, the best alternative is U_3 and the worst alternative is U_5 .

In Step 8 of the improved EDAS algorithm, DMs can customize the value of φ with their different opinions for both positive and negative distances. In order to look at the influence of different preference values on ranking results, we

give various values of φ to determine the results in terms of the ranking of the alternatives, which are listed in Table 11.

Table 11 shows that the results of alternative rankings are consistent for $\varphi < 0.8$ and $\varphi \geq 0.8$. On the contrary, the ranking for $\varphi \geq 0.8$ is slightly different from that for $\varphi < 0.8$. When $\varphi < 0.8$, the best alternative is U_3 and the worst alternative is U_5 . Whereas when $\varphi \geq 0.8$, the best alternative is U_2 and the worst alternative is U_5 . The best alternative is U_3 or U_2 , and it depends on the value of φ . Meanwhile, the worst case always U_5 for all φ values. So, the results are stable even though the value of φ is different.

When we compare with the original EDAS in [35] that assigned the constant value of φ to 0.5, the improved EDAS method allows DMs to adjust parameter φ in an interval 0 to 1. It takes the preference of DMs into account for loss and gains to the average ideal solution by adjusting the values of φ . The DMs can freely change the value of φ according to their judgments to obtain an acceptable solution in the genuine decision-making problem.

4.2. Comparative Analysis

4.2.1. Comparison with the BNNWA and BNNWG Operators. In this section, we attempt to compare results based on either in term ranking order or final score values with other approaches. We perform two comparative analyses. First, we compare the results between the improved EDAS using BNNWA and BNNWG operators. Second, the results provided by BNN-EDAS were also compared with the score function values of BNN that aggregated by BNNWA and BNNWG operators.

In the previous section, we utilize the BNNWA operator to fuse the evaluated linguistic values of DMs, and in this section, we attempt to reaggregate them by using another operator (BNNWG operator). Due to Steps 1 and 2 are the steps to transforming and normalizing the information from linguistic terms into BNNs, we skip these steps and continue to perform the selection process from Step 3 to Step 9. Similar to the previous section, we can acquire the appraisal score and a list of alternatives ranking order using the BNNWG operator, as demonstrated in Table 12.

Table 12 shows that the values of the appraisal score between using BNNWA and BNNWG operators are very slightly different, but the list of alternatives ranking order is a bit different. With the BNNWA operator, the alternative U_4 and U_1 are the third and the fourth position, respectively. Meanwhile, the EDAS with the BNNWG operator yields the two alternatives in swapped order.

Furthermore, we analyze the results obtained by the improved EDAS with the score function values of aggregated BNN. Based on Step 3 in Section 4.1, we utilize equation (7) for the BNNWA operator and equation (8) for the BNNWG operator to aggregate the evaluated BNN values of DMs. Afterward, we determine the weighted BNN matrix based on the aggregated BNN matrix and the weight matrix of criteria \mathcal{W} and then convert them into crisp values by calculating their score function values using Definition 6. Table 13 demonstrates the matrices of weighted BNN using

TABLE 1: The linguistic variable under bipolar neutrosophic numbers.

Linguistic variable	Bipolar neutrosophic numbers
Excessively high (EH)	$\langle 0.9, 0.15, 0, 0, -0.85, -0.95 \rangle$
Very high (VH)	$\langle 1, 0, 0.15, -0.25, -0.85, -0.95 \rangle$
Midst high (MH)	$\langle 0.85, 0.55, 0.65, -0.15, -0.85, -0.95 \rangle$
Enough (E)	$\langle 0.75, 0.65, 0.55, -0.25, -0.55, -0.65 \rangle$
Not enough (NE)	$\langle 0.55, 0.25, 0.35, -0.35, -0.15, -0.35 \rangle$
Low (L)	$\langle 0.45, 0.45, 0.35, -0.55, -0.25, -0.15 \rangle$
Midst low (ML)	$\langle 0.35, 0.15, 0.95, -0.45, -0.25, -0.15 \rangle$
Very low (VL)	$\langle 0.25, 0.35, 0.45, -0.85, -0.65, -0.45 \rangle$
Excessively low (EL)	$\langle 0.15, 0.95, 0.85, -0.95, -0.25, -0.15 \rangle$

TABLE 2: The evaluated linguistic values of decision maker DM₁.

	C ₁	C ₂	C ₃	C ₄
U ₁	E	ML	EH	EL
U ₂	EL	VH	E	L
U ₃	EH	NE	ML	VH
U ₄	NE	L	MH	VL
U ₅	EH	E	EH	EL

TABLE 3: The evaluated linguistic values of decision maker DM₂.

	C ₁	C ₂	C ₃	C ₄
U ₁	ML	VH	VL	E
U ₂	NE	E	ML	EH
U ₃	MH	EH	NE	MH
U ₄	EL	VL	EL	EH
U ₅	ML	EH	VH	ML

TABLE 4: The evaluated linguistic values of decision maker DM₃.

	C ₁	C ₂	C ₃	C ₄
U ₁	L	EH	E	EH
U ₂	MH	EH	ML	L
U ₃	VH	EL	E	L
U ₄	NE	MH	VH	MH
U ₅	ML	NE	MH	EH

BNNWA and BNNWG operators and their score function values, and Table 14 shows their comparison results.

Again, the results show that the ranking order of alternatives provided by BNNWA and BNNWG operators are the same as the results evaluated by the improved EDAS with the BNNWG operator. It indicates that the improved EDAS is applicable, effective, and practical for the MCGDM problem. The comparison results in terms of alternatives ranking order for these four approaches can be seen in Figure 2.

4.2.2. Comparison with the VIKOR Method for BNNs. In this section, we compared our improved EDAS method with the VIKOR [40] method for bipolar neutrosophic information. Pramanik et al. [40] designed an extended VIKOR method with MCGDM strategy for tackling bipolar neutrosophic information. We use the same data as in Table 5 to perform the comparative analysis.

In Step 6 of the VIKOR [40] algorithm, we adjusted the value of γ with the same values given to the value of ϕ in our proposed EDAS method. The results are shown in Table 15.

From Table 15, we can observe that the worst alternative is U₅ and the best one is U₃ for $\gamma = 0.1$, the worst alternative is U₄ and the best is U₃ for $0.2 \leq \gamma \leq 0.5$, the worst alternative is U₂ and the best is U₁ for $\gamma = 0.6$, and the worst alternative is U₂ and the best is U₅ for $\gamma \geq 0.7$. The results of alternative rankings are inconsistent.

The two methods have different ways to tackle the MCGDM with BNNs. The improved EDAS method calculates the distance of each alternative from the average ideal solution, which is used to rank alternatives in descending order. The VIKOR method in [40] used the value of the VIKOR index to determine the best alternative according to the result of alternative ranking in ascending order. On the contrary, the VIKOR method is not suitable for dealing with

TABLE 5: The normalized values of decision maker DM_k for alternative U_i with corresponding to criterion C_j .

	C_1	C_2	C_3	C_4	
DM ₁	U_1	$\langle 0.75, 0.65, 0.55, -0.25, -0.55, -0.65 \rangle$	$\langle 0.35, 0.15, 0.95, -0.45, -0.25, -0.15 \rangle$	$\langle 0.1, 0.85, 1, -1, -0.15, -0.05 \rangle$	$\langle 0.15, 0.95, 0.85, -0.95, -0.25, -0.15 \rangle$
	U_2	$\langle 0.15, 0.95, 0.85, -0.95, -0.25, -0.15 \rangle$	$\langle 1, 0, 0.15, -0.25, -0.85, -0.95 \rangle$	$\langle 0.25, 0.35, 0.45, -0.75, -0.45, -0.35 \rangle$	$\langle 0.45, 0.45, 0.35, -0.55, -0.25, -0.15 \rangle$
	U_3	$\langle 0.9, 0.15, 0, 0, -0.85, -0.95 \rangle$	$\langle 0.55, 0.25, 0.35, -0.35, -0.15, -0.35 \rangle$	$\langle 0.65, 0.85, 0.05, -0.55, -0.75, -0.85 \rangle$	$\langle 1, 0, 0.15, -0.25, -0.85, -0.95 \rangle$
	U_4	$\langle 0.55, 0.25, 0.35, -0.35, -0.15, -0.35 \rangle$	$\langle 0.45, 0.45, 0.35, -0.55, -0.25, -0.15 \rangle$	$\langle 0.15, 0.45, 0.35, -0.85, -0.15, -0.05 \rangle$	$\langle 0.25, 0.35, 0.45, -0.85, -0.65, -0.45 \rangle$
	U_5	$\langle 0.9, 0.15, 0, 0, -0.85, -0.95 \rangle$	$\langle 0.75, 0.65, 0.55, -0.25, -0.55, -0.65 \rangle$	$\langle 0.1, 0.85, 1, -1, -0.15, -0.05 \rangle$	$\langle 0.15, 0.95, 0.85, -0.95, -0.25, -0.15 \rangle$
DM ₂	U_1	$\langle 0.35, 0.15, 0.95, -0.45, -0.25, -0.15 \rangle$	$\langle 1, 0, 0.15, -0.25, -0.85, -0.95 \rangle$	$\langle 0.75, 0.65, 0.55, -0.15, -0.35, -0.55 \rangle$	$\langle 0.75, 0.65, 0.55, -0.25, -0.55, -0.65 \rangle$
	U_2	$\langle 0.55, 0.25, 0.35, -0.35, -0.15, -0.35 \rangle$	$\langle 0.75, 0.65, 0.55, -0.25, -0.55, -0.65 \rangle$	$\langle 0.65, 0.85, 0.05, -0.55, -0.75, -0.85 \rangle$	$\langle 0.9, 0.15, 0, 0, -0.85, -0.95 \rangle$
	U_3	$\langle 0.85, 0.55, 0.65, -0.15, -0.85, -0.95 \rangle$	$\langle 0.9, 0.15, 0, 0, -0.85, -0.95 \rangle$	$\langle 0.45, 0.75, 0.65, -0.65, -0.85, -0.65 \rangle$	$\langle 0.85, 0.55, 0.65, -0.15, -0.85, -0.95 \rangle$
	U_4	$\langle 0.15, 0.95, 0.85, -0.95, -0.25, -0.15 \rangle$	$\langle 0.25, 0.35, 0.45, -0.85, -0.65, -0.45 \rangle$	$\langle 0.85, 0.05, 0.15, -0.05, -0.75, -0.85 \rangle$	$\langle 0.9, 0.15, 0, 0, -0.85, -0.95 \rangle$
	U_5	$\langle 0.35, 0.15, 0.95, -0.45, -0.25, -0.15 \rangle$	$\langle 0.9, 0.15, 0, 0, -0.85, -0.95 \rangle$	$\langle 0, 1, 0.85, -0.75, -0.15, -0.05 \rangle$	$\langle 0.35, 0.15, 0.95, -0.45, -0.25, -0.15 \rangle$
DM ₃	U_1	$\langle 0.45, 0.45, 0.35, -0.55, -0.25, -0.15 \rangle$	$\langle 0.9, 0.15, 0, 0, -0.85, -0.95 \rangle$	$\langle 0.25, 0.35, 0.45, -0.75, -0.45, -0.35 \rangle$	$\langle 0.9, 0.15, 0, 0, -0.85, -0.95 \rangle$
	U_2	$\langle 0.85, 0.55, 0.65, -0.15, -0.85, -0.95 \rangle$	$\langle 0.9, 0.15, 0, 0, -0.85, -0.95 \rangle$	$\langle 0.65, 0.85, 0.05, -0.55, -0.75, -0.85 \rangle$	$\langle 0.45, 0.45, 0.35, -0.55, -0.25, -0.15 \rangle$
	U_3	$\langle 1, 0, 0.15, -0.25, -0.85, -0.95 \rangle$	$\langle 0.15, 0.95, 0.85, -0.95, -0.25, -0.15 \rangle$	$\langle 0.25, 0.35, 0.45, -0.75, -0.45, -0.35 \rangle$	$\langle 0.45, 0.45, 0.35, -0.55, -0.25, -0.15 \rangle$
	U_4	$\langle 0.55, 0.25, 0.35, -0.35, -0.15, -0.35 \rangle$	$\langle 0.85, 0.55, 0.65, -0.15, -0.85, -0.95 \rangle$	$\langle 0, 1, 0.85, -0.75, -0.15, -0.05 \rangle$	$\langle 0.85, 0.55, 0.65, -0.15, -0.85, -0.95 \rangle$
	U_5	$\langle 0.35, 0.15, 0.95, -0.45, -0.25, -0.15 \rangle$	$\langle 0.55, 0.25, 0.35, -0.35, -0.15, -0.35 \rangle$	$\langle 0.15, 0.45, 0.35, -0.85, -0.15, -0.05 \rangle$	$\langle 0.9, 0.15, 0, 0, -0.85, -0.95 \rangle$

TABLE 6: The aggregated BNN matrix using the BNNWA operator.

	C_1	C_2	C_3	C_4
U_1	$\langle 0.565, 0.358, 0.575, -0.384, -0.379, -0.387 \rangle$	$\langle 1, 0, 0, 0, -0.727, -0.857 \rangle$	$\langle 0.441, 0.596, 0.646, -0.49, -0.317, -0.337 \rangle$	$\langle 0.701, 0.481, 0, 0, -0.609, -0.728 \rangle$
U_2	$\langle 0.59, 0.519, 0.585, -0.392, -0.517, -0.667 \rangle$	$\langle 1, 0, 0, 0, -0.784, -0.904 \rangle$	$\langle 0.535, 0.612, 0.112, -0.616, -0.665, -0.741 \rangle$	$\langle 0.686, 0.313, 0, 0, -0.559, -0.666 \rangle$
U_3	$\langle 1, 0, 0, 0, -0.85, -0.95 \rangle$	$\langle 0.668, 0.315, 0, 0, -0.538, -0.697 \rangle$	$\langle 0.489, 0.624, 0.225, -0.637, -0.732, -0.691 \rangle$	$\langle 1, 0, 0.313, -0.267, -0.756, -0.883 \rangle$
U_4	$\langle 0.444, 0.388, 0.469, -0.486, -0.184, -0.289 \rangle$	$\langle 0.587, 0.439, 0.457, -0.43, -0.64, -0.685 \rangle$	$\langle 0.496, 0.276, 0.345, -0.321, -0.432, -0.483 \rangle$	$\langle 0.761, 0.303, 0, 0, -0.794, -0.878 \rangle$
U_5	$\langle 0.674, 0.15, 0, 0, -0.586, -0.702 \rangle$	$\langle 0.779, 0.3, 0, 0, -0.621, -0.778 \rangle$	$\langle 0.084, 0.741, 0.691, -0.866, -0.15, -0.05 \rangle$	$\langle 0.59, 0.296, 0, 0, -0.537, -0.636 \rangle$

TABLE 7: The aggregated BNN matrix using the BNNWG operator.

	C_1	C_2	C_3	C_4
U_1	$\langle 0.5, 0.462, 0.756, -0.419, -0.334, -0.258 \rangle$	$\langle 0.657, 0.103, 0.687, -0.271, -0.54, -0.479 \rangle$	$\langle 0.255, 0.691, 1, -1, -0.275, -0.197 \rangle$	$\langle 0.436, 0.777, 0.619, -0.699, -0.468, -0.423 \rangle$
U_2	$\langle 0.387, 0.763, 0.686, -0.727, -0.304, -0.345 \rangle$	$\langle 0.881, 0.326, 0.276, -0.182, -0.736, -0.838 \rangle$	$\langle 0.456, 0.741, 0.223, -0.637, -0.62, -0.612 \rangle$	$\langle 0.565, 0.365, 0.25, -0.414, -0.374, -0.275 \rangle$
U_3	$\langle 0.911, 0.276, 0.326, -0.13, -0.85, -0.95 \rangle$	$\langle 0.438, 0.653, 0.517, -0.652, -0.309, -0.377 \rangle$	$\langle 0.432, 0.724, 0.42, -0.652, -0.67, -0.596 \rangle$	$\langle 0.745, 0.357, 0.414, -0.329, -0.588, -0.546 \rangle$
U_4	$\langle 0.358, 0.693, 0.599, -0.721, -0.177, -0.264 \rangle$	$\langle 0.448, 0.452, 0.489, -0.621, -0.494, -0.374 \rangle$	$\langle 0, 1, 0.542, -0.678, -0.255, -0.127 \rangle$	$\langle 0.55, 0.364, 0.415, -0.527, -0.769, -0.72 \rangle$
U_5	$\langle 0.496, 0.15, 0.848, -0.313, -0.393, -0.296 \rangle$	$\langle 0.725, 0.41, 0.346, -0.209, -0.43, -0.611 \rangle$	$\langle 0, 1, 1, -1, -0.15, -0.05 \rangle$	$\langle 0.339, 0.702, 0.815, -0.729, -0.36, -0.26 \rangle$

TABLE 8: The average solution matrix \mathcal{AV} .

	C_1	C_2	C_3	C_4
\widetilde{av}_j	$\langle 1, 0, 0, 0, -0.567, -0.707 \rangle$	$\langle 1, 0, 0, 0, -0.673, -0.804 \rangle$	$\langle 0.428, 0.542, 0.33, -0.557, -0.505, -0.518 \rangle$	$\langle 1, 0, 0, 0, -0.668, -0.784 \rangle$

TABLE 9: The score function values of x_{ij} and \widetilde{av}_j .

	C_1	C_2	C_3	C_4
U_1	0.50	0.93	0.39	0.76
U_2	0.55	0.95	0.60	0.77
U_3	0.97	0.76	0.57	0.84
U_4	0.43	0.60	0.58	0.86
U_5	0.80	0.81	0.16	0.74
$S(\widetilde{av}_j)$	0.88	0.91	0.50	0.91

TABLE 10: The matrix of PDA and NDA.

		C_1	C_2	C_3	C_4
PDA	U_1	0	0.0195	0	0
	U_2	0	0.0385	0.1912	0
	U_3	0.0996	0	0.1330	0
	U_4	0	0	0.1472	0
	U_5	0	0	0	0
NDA	U_1	0.4284	0	0.2181	0.1642
	U_2	0.3784	0	0	0.1566
	U_3	0	0.1622	0	0.0723
	U_4	0.5117	0.3455	0	0.0588
	U_5	0.0874	0.1095	0.6741	0.1807

TABLE 11: The ranking results calculated by the improved EDAS method with different parameter values of φ .

	The best alternative	The worst alternative	Ranking
$\varphi = 0.1$	U_3	U_5	$U_3 > U_2 > U_4 > U_1 > U_5$
$\varphi = 0.2$	U_3	U_5	$U_3 > U_2 > U_4 > U_1 > U_5$
$\varphi = 0.3$	U_3	U_5	$U_3 > U_2 > U_4 > U_1 > U_5$
$\varphi = 0.4$	U_3	U_5	$U_3 > U_2 > U_4 > U_1 > U_5$
$\varphi = 0.5$	U_3	U_5	$U_3 > U_2 > U_4 > U_1 > U_5$
$\varphi = 0.6$	U_3	U_5	$U_3 > U_2 > U_4 > U_1 > U_5$
$\varphi = 0.7$	U_3	U_5	$U_3 > U_2 > U_4 > U_1 > U_5$
$\varphi = 0.8$	U_2	U_5	$U_2 > U_3 > U_4 > U_1 > U_5$
$\varphi = 0.9$	U_2	U_5	$U_2 > U_3 > U_4 > U_1 > U_5$

TABLE 12: The values of as_i and the ranking of alternatives.

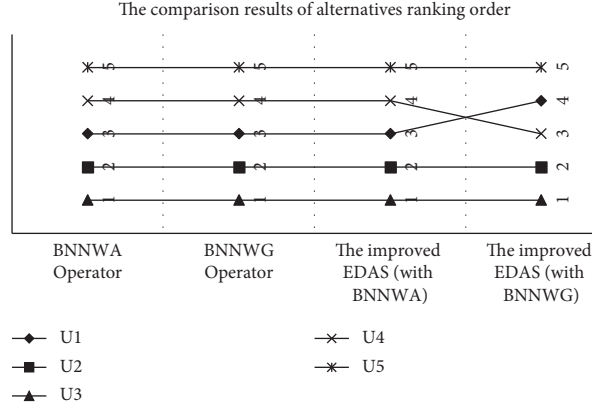
	as_1	as_2	as_3	as_4	as_5	Ranking
EDAS (with BNNWA)	0.2016	0.8266	0.9002	0.5475	0	$U_3 > U_2 > U_4 > U_1 > U_5$
EDAS (with BNNWG)	0.2190	0.779	0.8879	0.1839	0.0091	$U_3 > U_2 > U_1 > U_4 > U_5$

TABLE 13: The weighted group BNN matrix using BNNWA and BNNWG operators and their score function values.

	U_1	U_2	U_3	U_4	U_5
BNNWA	$\langle 1, 0, 0, -0.489, -0.582 \rangle$ $\delta(U_i)$ 0.8453	$\langle 1, 0, 0, 0, -0.65, -0.765 \rangle$ 0.9027	$\langle 1, 0, 0, 0, -0.745, -0.831 \rangle$ 0.9295	$\langle 0.556, 0.382, 0, 0, -0.512, -0.592 \rangle$ 0.7133	$\langle 0.528, 0.504, 0, 0, -0.448, -0.539 \rangle$ 0.6688
BNNWG	$\langle 0.395, 0.582, 1, -1, -0.358, -0.282 \rangle$ $\delta(U_i)$ 0.2425	$\langle 0.516, 0.649, 0.392, -0.573, -0.498, -0.501 \rangle$ 0.4832	$\langle 0.566, 0.582, 0.418, -0.517, -0.597, -0.603 \rangle$ 0.5414	$\langle 0.1, 0.53, -0.66, -0.313, -0.246 \rangle$ 0.2282	$\langle 0, 1, 1, -1, -0.268, -0.165 \rangle$ 0.0723

TABLE 14: The comparison results.

Methods	Ranking
The improved EDAS (with BNNWA)	$U_3 > U_2 > U_4 > U_1 > U_5$
The improved EDAS (with BNNWG)	$U_3 > U_2 > U_1 > U_4 > U_5$
BNNWA operator	$U_3 > U_2 > U_1 > U_4 > U_5$
BNNWG operator	$U_3 > U_2 > U_1 > U_4 > U_5$

FIGURE 2: The comparison results in terms of alternatives ranking order using $\varphi = 0.5$.TABLE 15: The ranking results calculated by the VIKOR method with different parameter values of γ .

	The best alternative	The worst alternative	Ranking
$\gamma = 0.1$	U_3	U_5	$U_3 > U_1 > U_2 > U_4 > U_5$
$\gamma = 0.2$	U_3	U_4	$U_3 > U_1 > U_2 > U_5 > U_4$
$\gamma = 0.3$	U_3	U_4	$U_3 > U_1 > U_2 > U_5 > U_4$
$\gamma = 0.4$	U_3	U_4	$U_3 > U_1 > U_5 > U_2 > U_4$
$\gamma = 0.5$	U_3	U_4	$U_3 > U_1 > U_5 > U_2 > U_4$
$\gamma = 0.6$	U_1	U_2	$U_1 > U_5 > U_3 > U_4 > U_2$
$\gamma = 0.7$	U_5	U_2	$U_5 > U_1 > U_3 > U_4 > U_2$
$\gamma = 0.8$	U_5	U_2	$U_5 > U_1 > U_3 > U_4 > U_2$
$\gamma = 0.9$	U_5	U_2	$U_5 > U_1 > U_4 > U_3 > U_2$

our MCGDM problem with bipolar neutrosophic information, while the improved EDAS method is stable and useful to handle the MCGDM problem.

5. Conclusion and Future Studies

The concept of BNNs is a suitable instrument in expressing the cases with vagueness, inconsistent, incomplete, and indeterminate information, which now widely prevail in various decision-making problems. In this manuscript, based on the original EDAS [35], we develop an improved EDAS for MCGDM problems described by BNNs. This method calculates the average alternative by aggregating the BNNs for each criterion using the BNNWA and BNNWG operators. Next, it calculates the positive and negative distances between each evaluated alternative and the average solution separately. After adjusting the parameter values of φ according to the DM preference, the improved EDAS method calculates the appraisal score and ranks alternatives. A case study to determine the best MSME in distributing the

PEE program is analyzed. This case study is applied to demonstrate that the proposed EDAS method is stable to yield ranking results of alternatives for different parameter values and is reasonable and feasible for handling MCGDM problems with BNNs by comparing with some aggregation BNN methods.

From the comparative analysis and the results of algorithm analysis presented in the previous section, it is clear that the proposed EDAS method requires less information preprocessing and less computation and is suitable to resolve the MCGDM problem with many conflicting criteria and alternatives. It can also be widely applied for the information described by IFs, bipolar fuzzy sets, SVNss, or MVNNs, which have similar forms with BNNs. Moreover, the improved EDAS method considers the DMs' preference for the loss or gain of an alternative, to get the most desired solution.

However, this approach only holds the case of given DMs' weight matrix and criteria' weight matrix; it does not address the unknown weight matrix. So, it will be a challenge in the future to establish some novel strategies to gain a more

realistic weight matrix and more rational decision results. Additionally, it is also important to develop the EDAS method based on some other neutrosophic sets and fuzzy sets, such as bipolar trapezoidal neutrosophic sets [41], complex intuitionistic uncertain linguistic Heronian mean [42], and triangular fuzzy neutrosophic set [43].

Data Availability

The data that support the findings of this study are available within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

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