A robust aggregation operators for multi-criteria decision-making method with bipolar fuzzy soft environment

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Abstract
Molodtsov initiated soft set theory that provided a general mathematical framework for handling with uncertainties in which we encounter the data by affix parameterized factor during the information analysis as differentiated to fuzzy as well as bipolar fuzzy set theory. The main object of this paper is to lay a foundation for providing a new application of bipolar fuzzy soft tool in considering many problems that contain uncertainties. In present study, aggregation of bipolar fuzzy soft numbers have so far not yet been applied for ranking of alternatives in decision-making problems. To this propose, bipolar fuzzy soft weighted arithmetic averaging (BFSWAA) operator, bipolar fuzzy soft weighted geometric averaging (BFSWGA) operator have been used to compare two bipolar fuzzy soft numbers (BFSNs) for aggregating different bipolar fuzzy soft input arguments in bipolar fuzzy soft environment. Then, their related properties have been investigated. Finally, a practical example for selection of alternatives is given to demonstrate the utility and application of the proposed work.

Keywords: Bipolar fuzzy soft numbers, Bipolar fuzzy soft arithmetic averaging operators, Bipolar fuzzy soft geometric averaging operators, Decision-making.

1 Introduction
Molodtsov introduced soft set theory for modeling uncertainties and vagueness of data. Many researchers studying on problems involving uncertainty have interested soft set theory since it was introduced by Molodtsov. The traditional tools are not only limited to fuzzy set theory and intuitionistic fuzzy set theory etc., but also widely used by the researchers in MADM problems, MCDM problems in intuitionistic fuzzy (IF) and interval-valued intuitionistic fuzzy IVIFS environments to overcome the uncertainties in real world problems. Although, IFS and IVIFS successfully applied to solve the uncertainty of the real world problems, but it has been seen generally for the information analysis of an object that corresponding to each property there exists a counter property. In that view, Zhang lately originated other generalization of fuzzy sets, called bipolar fuzzy sets (BFS) whose membership degree extended to [−1, 1]. Then BFS treated as a new tool to depict uncertainty in decision science. Bipolar fuzzy sets have not only been applied in bipolar logical reasoning and bipolar set theory but also have applications in different uncertain environments such as computational psychiatry, medicine science, bipolar quantum logic based computing, quantum cellular combinatorics, decision analysis and organizational modeling, physics and philosophy and bipolar fuzzy graph and its applications. Sing and Kumar have some applications of bipolar information using lattice theory, bipolar fuzzy graph as well as Formal Concept Analysis (FCA). Han et al. studied applications of decision information system in bipolar rough fuzzy environment. Lately, Gul provided concept of bipolar fuzzy aggregation operators, for example, bipolar fuzzy weighted averaging operator (BFWAA) and bipolar fuzzy weighted geometric operator (BFWGA) and applied these operators to study multiple
attribute group decision-making problems. Lu et al. 31 proposed linguistic aggregation operator on bipolar fuzzy numbers and gave an example of MADM problems using these operators. Wei et al. 32 utilized interval-valued bipolar 2-tuple linguistic (IVB2TLNs) arithmetic and geometric aggregation operators to investigate for the risk evaluation of enterprise human capital investment by a MADM problem. Wei et al. 32 studied recently a MADM problems based on bipolar fuzzy Hamacher aggregation operator. After that, Wei et al. 33 investigated the MADM problems under the aggregation operators based on hesitant bipolar fuzzy information. Xu and Wei 34 provided a multiple-attribute decision-making problems based on dual hesitant bipolar fuzzy aggregation function. Khalid and Beg 35 used preference relations based decision-making in incomplete interval-valued hesitant fuzzy environment. Gao et al. 36 used Hamacher prioritized aggregation operators on dual hesitant bipolar fuzzy numbers, and develop a MADM problem for analyzed the relevance and effectiveness of the proposed method. Wan et al. 31 introduced Frank Choquet Bonferroni mean operators and utilized this operator develop MCDM problems in single-valued bipolar neutrosophic environment.

But the technique of the above papers are not enough for the solution of real-world problems because they have insufficient of parameterizations. In that view, soft set theory plays an important role to overcome such barrier and effectively applied to solve the conditions. Maji et al. 31, 32 provided the concept of “fuzzy soft sets” and “intuitionistic fuzzy soft sets” where soft set theory is combined with the fuzzy set theory and intuitionistic fuzzy set theory. Some hybrid models together with soft set theory have been developed in various uncertain environments such as on fuzzy soft set theory with parameterizations 33, 34, 35, fuzzy soft expert sets 36, generalized intuitionistic fuzzy soft sets 37, 38, interval-valued intuitionistic fuzzy soft sets 39, 40 and its applications, Hesitant fuzzy soft sets 39. Further, researchers 41 provided applications of similarity measures using soft sets. Selvachandran and Peng 37 has found a modified TOPSIS method using vague parameterized vague soft set and gave its application in decision-making. Recently, Arora and Garg 42 provided a new approach of aggregation operator using parameterized factor in intuitionistic fuzzy soft environment. In the same time, a tool combination of bipolar fuzzy set and soft set have gave a momentum to the solution of real life problems in many directions. Karray and others 43, 44, 45 introduced bipolar soft group structures, soft rough relations and then used soft-rough relations to develop a decision-making problems. Abdullah et al. 46 gave an application of bipolar fuzzy soft sets in decision-making problem. Yang et al. 47 utilized bipolar multi-fuzzy soft set in decision-making approach. Qudah and Hassan 48 proposed bipolar fuzzy soft expert set and its application in decision-making. Ali et al. 49 gave an application of bipolar neutrosophic soft sets in decision-making in the environment of bipolar neutrosophic set. Akram et al. 3 provided bipolar fuzzy soft information with graph and then developed a multi criteria-decision making method based on bipolar fuzzy soft graphs.

Thus, BFSS is a powerful appliance to deal with the ambivalence and vagueness of data, the propose work will introduce a new aggregation operator known as bipolar fuzzy soft aggregation operators depicted as bipolar fuzzy soft weighted arithmetic averaging (BFSSWAA) operator and bipolar fuzzy soft weighted geometric average aggregation (BFSSWGA) operator in the environment of bipolar fuzzy soft numbers (BFSNs). The main advantages of these operators is that they are able to make smooth description of the real-world problems by the use of parameterizations factor. In order to rank the alternatives, aggregation operators lead to aggregate the over all information of the objects for the preferences of the decision maker into a collective one and hence find to a desirable according to its score values. To the best of our knowledge, the research developed on FSS and BFSS is only about their basic theory and its applications, but, there have been no research done on bipolar fuzzy soft aggregation information. So, it is a new issue and have a scope for future development in decision science. Above decision-making problems in bipolar fuzzy soft environment under aggregation operators makes us enough motivation to develop our present paper. The main object of this article is to exhibit some aggregation operators under bipolar fuzzy called as bipolar fuzzy soft aggregations for amassing the distinct priorities of the choices amid the decision-making process.

The remainder of this paper is sorted out as takes after: In next Section, we briefly survey some essential ideas of the FSS and BFSS. In Section 3, we define some operational principles of bipolar fuzzy soft numbers and then define bipolar fuzzy soft weighted arithmetic averaging (BFSSWAA) operator, bipolar fuzzy soft weighted geometric averaging (BFSSWGA) operator and established its related properties. In next section, we utilize those operators to create bipolar fuzzy soft multi-attribute decision-making problems. An interpretative case is specified for the selection of best candidate(s) for a company in Section 5. In section 6, a comparative analysis has been made between the existing works and the proposed study. Finally, in Section 7, the conclusion and scope of future research are outlined and discussed.
2 Basic concept of FSS and BFSS

In what follows, $U$, $E$ and $\mathcal{P}(U)$ denote initial universal set, set of parameters and power set of $U$, respectively. Also, $A \subseteq E$.

Definition 2.1. Let $X$ be a non-empty set. A fuzzy set $\mu$ of $X$ is defined as a mapping $\mu : X \rightarrow [0, 1]$, where $[0, 1]$ is the usual interval of real numbers. We take $\mathcal{F}(X)$ as the set of all fuzzy subsets of $X$.

Definition 2.2. A pair $(\mathcal{F}, E)$ is called a soft set over $U$ if $\mathcal{F}$ is a mapping given by $\mathcal{F} : E \rightarrow \mathcal{P}(U)$. In other words, a soft set over the universe $U$ is a parameterized family of subsets of the universe $U$. For $\varepsilon \in A$, $\mathcal{F}(\varepsilon)$ may be considered as the set of elements of the soft $(\mathcal{F}, A)$, or as the set of $\varepsilon$-approximate points of the soft set.

The following example illustrate the above idea.

Example 2.3. Let $(X, \tau)$ be a topological space, i.e., $\tau$ is a family of subsets of the set $X$ called the open sets of $X$. Then, the family of open neighborhood $N(x)$ of point $x$, where $N(x) = \{ V \mid x \in V \}$, may be consider as the soft set $(N(x), \tau)$.

Definition 2.4. Let $U$ be the universal set and $E$ be the set of parameters. Let $\mathcal{P}(U)$ be the power set of $U$ and $A \subseteq E$, and $\mathcal{P}(U)$ is the collection of all fuzzy subsets of $U$, then $(\mathcal{F}, A)$ is called fuzzy soft set, where $\mathcal{F} : A \rightarrow \mathcal{P}(U)$.

Example 2.5. Let $U = \{ M_1, M_2, M_3, M_4 \}$ be the set of four mobiles under consideration and $E = \{ \{ \text{beautiful}(e_1) \}, \{ \text{costly}(e_2) \}, \{ \text{battery backup}(e_3) \}, \{ \text{apps}(e_4) \} \}$ be a set of parameters then FSS for describing "attractiveness of the mobiles" is $(\mathcal{F}, A) = \{ \{ F_{e_1}, F_{e_2}, F_{e_3} \}, \text{where A = \{e_1, e_2, e_3\} \subseteq E and (F, A) can be defined as:} \}

\begin{align*}
F_{e_1} &= \{ \{ M_1 \}, \{ M_2 \}, \{ M_3 \}, \{ M_4 \} \},
F_{e_2} &= \{ \{ M_1 \}, \{ M_2 \}, \{ M_3 \}, \{ M_4 \} \},
F_{e_3} &= \{ \{ M_1 \}, \{ M_2 \}, \{ M_3 \}, \{ M_4 \} \}.
\end{align*}

Definition 2.6. A bipolar fuzzy sets (BFS) is defined over the universe of discourse $X$ as

$$B = \{ (x, \mu^+(x), \nu^-(x)) \mid x \in X \},$$

where $\mu^+(x) : X \rightarrow [0, 1]$ represent positive membership degree to satisfy corresponding property of an element $x$ to a BFS and $\nu^-(x) : X \rightarrow [-1, 0]$ represent negative membership degree to satisfy counter-property of an element $x$ to a BFS, such that $-1 \leq \mu^+(x) + \nu^-(x) \leq 1$ for every $x \in X$. The set $((\mu^+, \nu^-))$ is denote bipolar fuzzy numbers (BFNs), i.e., bipolar fuzzy elements (BFEs).

Definition 2.7. Let $U$ be a universal set, $E$ be a set of parameters and $A \subseteq E$. Define $\tilde{B} : A \rightarrow BF^U$, where $BF^U$ is the collection of all bipolar fuzzy subsets of $U$. Then $(\tilde{B}, A)$ is called bipolar fuzzy soft set over $U$, and is denoted by $(\tilde{B}, A) = B(e_1)$ and defined by

$$\tilde{B}(e_1) = \{ (x_1, \mu^+_1(x_1), \nu^-_1(x_1)) \mid x_1 \in U, \forall e_1 \in A \}.$$

Example 2.8. Let $U = \{ M_1, M_2, M_3, M_4 \}$ be the set of four mobiles under consideration and $E = \{ \{ \text{beautiful}(e_1) \}, \{ \text{costly}(e_2) \}, \{ \text{battery backup}(e_3) \}, \{ \text{apps}(e_4) \} \}$ be a set of parameters under BFSS for describing "attractiveness of the mobiles" is $(\tilde{B}, A) = \{ F_{e_1}, F_{e_2}, F_{e_3} \}, \text{where A = \{e_1, e_2, e_3\} \subseteq E and }\text{(\tilde{B}, A) can be defined as:}

\begin{align*}
\tilde{B}_{e_1} &= \{ (M_1, 0.6, -0.2), (M_2, 0.4, -0.1), (M_3, 0.5, -0.3), (M_4, 0.3, -0.1) \},
\tilde{B}_{e_2} &= \{ (M_1, 0.7, -0.2), (M_2, 0.6, -0.1), (M_3, 0.5, -0.3), (M_4, 0.4, -0.1) \} \text{and}
\tilde{B}_{e_3} &= \{ (M_1, 0.9, -0.3), (M_2, 0.5, -0.2), (M_3, 0.3, -0.1), (M_4, 0.6, -0.4) \}.
\end{align*}

For the sake of simplicity, we denote the pair of $\tilde{B}_{e_1}(x) = \{ (x, \mu^+_1(x), \nu^-_1(x)) \mid x \in U \}$, i.e., $\tilde{B}_{e_1} = (\mu^+_1, \nu^-_1)$ is called as bipolar fuzzy soft (BFSS) number. For the application purpose, it is necessary to define score function for ranking it. For this, a score function of $\tilde{B}_{e_1}$ is defined as

$$\Psi(\tilde{B}_{e_1}) = \mu^+_1 + \nu^-_1,$$

where, $\Psi(\tilde{B}_{e_1}) \in [-1, 1]$. By this definition, it is clear that the larger the $\Psi(\tilde{B}_{e_1})$, the larger is BFSN $\tilde{B}_{e_1}$.

Example 2.9. Let $\tilde{B}_{e_1} = \{ (0.6, -0.2) \} \text{ and } \tilde{B}_{e_2} = \{ (0.3, -0.5) \}$ be two BFSNs, then by eq.(2), we get $\Psi(\tilde{B}_{e_1}) = 0.4$ and $\Psi(\tilde{B}_{e_2}) = -0.2$. Since $\Psi(\tilde{B}_{e_1}) > \Psi(\tilde{B}_{e_2})$, which implies $\tilde{B}_{e_1} > \tilde{B}_{e_2}$.

However, there are some situations, where above function can not be used to compare BFSNs. For example, let $\tilde{B}_{e_1} = \{ (0.6, -0.2) \} \text{ and } \tilde{B}_{e_2} = \{ (0.5, -0.1) \}$, then it is not possible to compare BFSNs, which one of them is bigger as $\Psi(\tilde{B}_{e_1}) = \Psi(\tilde{B}_{e_2})$. To overcome this situation, we define accuracy function of $\tilde{B}_{e_1}$ as follows:

$$\mathcal{H}(\tilde{B}_{e_1}) = \mu^+_1 - \nu^-_1.$$
where, \( H(\tilde{B}_{e_t}) \in [0, 1] \). Based on score function \( \Psi \) and accuracy function \( H \), defined order relation on two BFSNs \( \tilde{B}_{e_t} \) and \( \tilde{P}_{e_t} \) as follows:

(i) If \( \Psi(\tilde{B}_{e_t}) < \Psi(\tilde{P}_{e_t}) \), then \( \tilde{B}_{e_t} \prec \tilde{P}_{e_t} \)
(ii) If \( \Psi(\tilde{B}_{e_t}) > \Psi(\tilde{P}_{e_t}) \), then \( \tilde{B}_{e_t} \succ \tilde{P}_{e_t} \)
(iii) If \( \Psi(\tilde{B}_{e_t}) = \Psi(\tilde{P}_{e_t}) \), then

(1) If \( H(\tilde{B}_{e_t}) < H(\tilde{P}_{e_t}) \), then \( \tilde{B}_{e_t} \prec \tilde{P}_{e_t} \).
(2) If \( H(\tilde{B}_{e_t}) > H(\tilde{P}_{e_t}) \), then \( \tilde{B}_{e_t} \succ \tilde{P}_{e_t} \).
(3) If \( H(\tilde{B}_{e_t}) = H(\tilde{P}_{e_t}) \), then \( \tilde{B}_{e_t} \sim \tilde{P}_{e_t} \).

3 Bipolar fuzzy soft weighted arithmetic averaging operator

In this section, an aggregation operators namely bipolar fuzzy soft weighted arithmetic averaging (BFSWAA) operator for bipolar fuzzy soft numbers (BFSNs) are proposed.

3.1 Operational law for BFSNs

**Definition 3.1.** Let \( \tilde{B}_e = (\mu^+, \nu^-) \) and \( \tilde{B}_{e_{11}} = (\mu^+_{11}, \nu^-_{11}) \) and \( \tilde{B}_{e_{12}} = (\mu^+_{12}, \nu^-_{12}) \) be the BFSNs over the universe \( X \), then following operations are defined as follows:

(i) \( \tilde{B}_{e_{11}} \oplus \tilde{B}_{e_{12}} = ((\mu^+_{11} + \mu^+_{12} - \mu^+_{11} \mu^+_{12}, -|\nu^-_{11}| \nu^-_{12})) \)

(ii) \( \tilde{B}_{e_{11}} \otimes \tilde{B}_{e_{12}} = ((\mu^+_{11} \mu^+_{12}, \nu^-_{11} + \nu^-_{12} - \nu^-_{11} \nu^-_{12})) \)

(iii) \( \lambda \tilde{B}_e = (1 - (1 - \mu^+)^\lambda, -|\nu^-|^\lambda) \)

(iv) \( \tilde{B}_e^\lambda = (\mu^+, -1 + (1 + \nu^-)^\lambda) \).

**Definition 3.2.** Let \( \tilde{B}_{e_{st}} = (\mu^+_{st}, \nu^-_{st}) \) \((s = 1, 2, \ldots, m; t = 1, 2, \ldots, n)\) be a collection of BFSNs and \( \phi_t, \theta_s \) are the weight vectors for the parameter \( e_t \)'s and expert \( y_s \)'s respectively, satisfying \( \phi_t \geq 0, \theta_s \geq 0 \) such that \( \sum_{t=1}^{n} \phi_t = 1 \) and \( \sum_{s=1}^{m} \theta_s = 1 \). Then bipolar fuzzy soft weighted arithmetic averaging (BFSWAA) operator is function \( BFSWA: \tilde{B}^n \rightarrow \tilde{B} \) such that

\[
BFSWAA(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{mn}}) = \bigoplus_{t=1}^{n} \phi_t \left( \bigotimes_{s=1}^{m} \theta_s \tilde{B}_{e_{st}} \right).
\]

We get the following theorem that follows on BFSWAA operator.

**Theorem 3.3.** \( \tilde{B}_{e_{st}} = (\mu^+_{st}, \nu^-_{st}) \) \((s = 1, 2, \ldots, m; t = 1, 2, \ldots, n)\) be a collection of (BFSNs), then aggregated value of them using the BFSWAA operator is also a BFSNs, and

\[
BFSWA(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{mn}}) = \left( 1 - \prod_{t=1}^{n} \left( \frac{m}{s=1} (1 - \mu^+_{st})^{\phi_t} \right)^{\phi_t}, -\prod_{t=1}^{n} \left( \frac{m}{s=1} |\nu^-_{st}|^{\theta_s} \right)^{\theta_t} \right).
\]

Then Theorem 3.3 can be proved by the method of mathematical induction as follows.

**Proof:** For \( m = 1 \), we get \( \theta_1 = 1 \). Then by Definition 3.1 of operational law,

\[
BFSWAA(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{mn}}) = \bigoplus_{t=1}^{n} \phi_t \left( \tilde{B}_{e_{11}} \right) = \left( 1 - \prod_{t=1}^{n} \left( 1 - \mu^+_{11} \right)^{\phi_t}, -\prod_{t=1}^{n} \left( \frac{1}{s=1} |\nu^-_{11}|^{\theta_t} \right)^{\theta_t} \right).
\]
Again, for \( n = 1 \) and \( \phi_1 = 1 \) and hence,

\[
\text{BFSWAA}(\hat{B}_{c_1}, \hat{B}_{c_2}, \ldots, \hat{B}_{c_m}) = \left( \bigoplus_{s=1}^{m} \theta_{s1} \hat{B}_{c_{st}} \right)
\]

\[
= \left( 1 - \prod_{t=1}^{m} \left( 1 - \mu_{st}^{+} \right)^{\theta_t} \right), \prod_{s=1}^{m} |\nu_{s1}|^{\theta_t}
\]

\[
= \left( 1 - \prod_{t=1}^{m} \left( \prod_{s=1}^{m} \left( 1 - \mu_{st}^{+} \right)^{\theta_t} \right)^{\phi_t}, - \prod_{t=1}^{m} \left( \prod_{s=1}^{m} |\nu_{st}|^{\theta_t} \right)^{\phi_t} \right).
\]

Thus, (5) is true for \( m = 1 \) and \( n = 1 \). Assume that (5) is true for \( n = p_1 + 1, m = p_2 \) and \( n = p_1, m = p_2 + 1 \), then it follows that

\[
\bigoplus_{t=1}^{p_1+1} \phi_t \left( \bigoplus_{s=1}^{p_2+1} \theta_s \hat{B}_{c_{st}} \right) = \left( 1 - \prod_{t=1}^{p_1+1} \left( \prod_{s=1}^{p_2+1} \left( 1 - \mu_{st}^{+} \right)^{\theta_t} \right)^{\phi_t}, - \prod_{t=1}^{p_1+1} \left( \prod_{s=1}^{p_2+1} |\nu_{st}|^{\theta_t} \right)^{\phi_t} \right).
\]

Also,

\[
\bigoplus_{t=1}^{p_1} \phi_t \left( \bigoplus_{s=1}^{p_2+1} \theta_s \hat{B}_{c_{st}} \right) = \left( 1 - \prod_{t=1}^{p_1} \left( \prod_{s=1}^{p_2+1} \left( 1 - \mu_{st}^{+} \right)^{\theta_t} \right)^{\phi_t}, - \prod_{t=1}^{p_1} \left( \prod_{s=1}^{p_2+1} |\nu_{st}|^{\theta_t} \right)^{\phi_t} \right).
\]

Now for \( n = p_1 + 1 \) and \( m = p_2 + 1 \), we obtained

\[
\bigoplus_{t=1}^{p_1+1} \phi_t \left( \bigoplus_{s=1}^{p_2+1} \theta_s \hat{B}_{c_{st}} \right) = \left( 1 - \prod_{t=1}^{p_1+1} \left( \prod_{s=1}^{p_2} \left( 1 - \mu_{st}^{+} \right)^{\theta_t} \right)^{\phi_t} \right), \prod_{s=1}^{p_2+1} \left( 1 - \mu_{(p_2+1)t}^{+} \right)^{\theta_t}, \prod_{s=1}^{p_2+1} \left( 1 - \mu_{(p_2+1)t}^{+} \right)^{\theta_t} \right)
\]

\[
= \left( 1 - \prod_{t=1}^{p_1+1} \left( \prod_{s=1}^{p_2} \left( 1 - \mu_{st}^{+} \right)^{\theta_t} \right)^{\phi_t} \right), \prod_{s=1}^{p_2+1} \left( 1 - \mu_{(p_2+1)t}^{+} \right)^{\theta_t}, \prod_{s=1}^{p_2+1} \left( 1 - \mu_{(p_2+1)t}^{+} \right)^{\theta_t} \right).
\]

Thus, (5) is true for \( n = p_1 + 1, m = p_2 + 1 \), therefore by induction the results is hold for all \( m, n \geq 1 \).

Since, \( 0 \leq \mu_{st}^{+} \leq 1 \iff 0 \leq \prod_{t=1}^{m} \left( 1 - \mu_{st}^{+} \right)^{\theta_t} \leq 1 \) and hence, \( 0 \leq 1 - \prod_{t=1}^{n} \left( 1 - \mu_{st}^{+} \right)^{\phi_t} \leq 1 \). Also, \( -1 \leq \nu_{st}^{-} \leq 0 \iff 0 \leq |\nu_{st}^{-}| \leq 1 \iff -1 \leq -|\nu_{st}^{-}| \leq 0 \iff -1 \leq -\prod_{t=1}^{n} \left| \nu_{st}^{-} \right|^{\phi_t} \leq 0 \iff -1 \leq -\prod_{t=1}^{n} \prod_{s=1}^{m} \left| \nu_{st}^{-} \right|^{\phi_t} \leq 0 \). Thus,

\[
1 \geq 1 - \prod_{t=1}^{n} \prod_{s=1}^{m} \left( \prod_{t=1}^{n} \left( 1 - \mu_{st}^{+} \right)^{\phi_t} \right) - \prod_{t=1}^{n} \prod_{s=1}^{m} \left| \nu_{st}^{-} \right|^{\phi_t} = 1 - \prod_{t=1}^{n} \left( \prod_{s=1}^{m} \left( 1 - \mu_{st}^{+} \right)^{\phi_t} \right) - \prod_{t=1}^{n} \prod_{s=1}^{m} \left( \left| \nu_{st}^{-} \right|^{\phi_t} - 1 \right) \phi_t \geq -1.
\]

Hence, aggregated value obtained by BFSWAA is again a BFSN.

\[ \Box \]

**Corollary 3.4.** \( \Box \) For only one parameter \( e_1 \), i.e., \( n = 1 \), then BFSWAA operator reduces to BFWA.

\[
\text{BFSWAA}(\hat{B}_{c_{e_1}}, \hat{B}_{c_{e_2}}, \ldots, \hat{B}_{c_{e_m}}) = \left( 1 - \prod_{s=1}^{m} \left( 1 - \mu_{s1}^{+} \right)^{\theta_s}, - \prod_{s=1}^{m} \left| \nu_{s1}^{-} \right|^{\phi_s} \right).
\]

Therefore, it is justified that aggregation operator defined under BFS environment is taken as a special case of the proposed operator.

**Example 3.5.** Let \( Y = \{y_1, y_2, y_3, y_4\} \) be the set of experts which are going to narrate the “attractiveness of two-wheeler bikes” under the set of parameters \( E = \{e_1 = \text{stylish}, e_2 = \text{weight}, e_3 = \text{milage}, e_4 = \text{price}\} \). The rating value of the
Theorem 3.6. (Idempotency Property) Let \( \tilde{B}_{e_t} = (\mu^+_s, \nu^-_s) \) \((s = 1, 2, \ldots, m; t = 1, 2, \ldots, n)\) be a collection of BFSNs. Let \( B_{e_t} = (\mu^+_s, \nu^-_s) \) and \( \tilde{B}_{e_t} = (\mu^+_s, \nu^-_s) \). Then,

\[
BFSWAA(\tilde{B}_{e_1}, \tilde{B}_{e_2}, \ldots, \tilde{B}_{e_m}) = \tilde{B}_e.
\]

Proof: Since \( \tilde{B}_{e_t} = \tilde{B}_e = (\mu^+, \nu^-) \) for all \( s, t \), then,

\[
BFSWAA(\tilde{B}_{e_1}, \tilde{B}_{e_2}, \ldots, \tilde{B}_{e_m}) = \left< 1 - \prod_{t=1}^{n} \left( \prod_{s=1}^{m} (1 - \mu^+_{st})^{\phi_t} \right), \prod_{t=1}^{n} \left( \prod_{s=1}^{m} \nu^-_{st}^{\phi_t} \right) \right>
\]

\[
= \left< 1 - \left( (1 - \mu^+_{11})^{\phi_1} \right)^{\sum_{t=1}^{n} \phi_t}, \left( \prod_{s=1}^{m} \nu^-_{st}^{\phi_t} \right) \right>
\]

\[
= \left< 1 - (1 - \mu^+), \nu^- \right>
\]

= \( \left< \mu^+, \nu^- \right> \).

The proof is completed.

\[\square\]

Theorem 3.7. (Boundedness Property) Let \( \tilde{B}_{e_t} = (\mu^+_s, \nu^-_s) \) \((s = 1, 2, \ldots, m; t = 1, 2, \ldots, n)\) be a collection of BFSNs. Let \( B_{e_t} = (\min \\min \{\mu^+_s\}, \max \\max \{\nu^-_s\}) \) and \( \tilde{B}_{e_t} = (\max \\max \{\mu^+_s\}, \min \\min \{\nu^-_s\}) \). Then,

\[
B_{e_t} \leq BFSWAA(\tilde{B}_{e_1}, \tilde{B}_{e_2}, \ldots, \tilde{B}_{e_m}) \leq B_{e_t}.
\]

Proof: Since \( \tilde{B}_{e_t} = (\mu^+_s, \nu^-_s) \) be a BFSNs then \( \min \\min \{\mu^+_s\} \leq \mu^+_s \leq \max \\max \{\mu^+_s\} \) which implies that \( 1 - \max \\max \{\mu^+_s\} \leq 1 - \mu^+_s \leq 1 - \min \\min \{\mu^+_s\} \) \( \iff \) \( (1 - \max \\max \{\mu^+_s\})^{\phi_t} \leq (1 - \mu^+_s) \leq (1 - \min \\min \{\mu^+_s\})^{\phi_t} \) \( \iff \) \( 1 - \max \\max \{\mu^+_s\} \) \( \leq \prod_{t=1}^{n} (1 - \mu^+_{st})^{\phi_t} \leq 1 - \min \\min \{\mu^+_s\} \).

\[
\max \\max \{\mu^+_s\} \leq \prod_{t=1}^{n} (1 - \mu^+_{st})^{\phi_t} \leq 1 - \min \\min \{\mu^+_s\}. \tag{8}
\]
Again, \( \min \min_{t,s} \{ \nu_{st}^- \} \leq \nu_{st}^- \leq \max \max_{t,s} \{ \nu_{st}^- \} \)

which finds \( \left( \min \min_{t,s} \{ \nu_{st}^- \} \right)^{\sum_{t=1}^{m} \phi_t} \leq \prod_{t=1}^{m} (\nu_{st}^-)^{\phi_t} \leq \left( \max \max_{t,s} \{ \nu_{st}^- \} \right)^{\sum_{t=1}^{m} \phi_t} \)

hence we get,

\[
\min \min_{t,s} \{ \nu_{st}^- \} \leq \prod_{t=1}^{m} \left( \prod_{s=1}^{n} (\nu_{st}^-)^{\phi_t} \right) \leq \max \max_{t,s} \{ \nu_{st}^- \}.
\]

(9)

Let \( \beta \equiv BFSWAA(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{emn}}) = (\mu_{\beta}^+, \nu_{\beta}^-) \), then from Eqs. (8) and (9), \( \min \min_{t,s} \{ \nu_{st}^+ \} \leq \mu_{\beta}^+ \leq \max \max_{t,s} \{ \nu_{st}^- \} \)

and \( \min \min_{t,s} \{ \nu_{st}^- \} \leq \nu_{\beta}^- \leq \max \max_{t,s} \{ \nu_{st}^- \} \).

Then by definition of score function

\[
\Psi(\beta) = \mu_{\beta}^+ + \nu_{\beta}^- \leq \max \max_{t,s} \{ \nu_{st}^+ \} + \min \min_{t,s} \{ \nu_{st}^- \} = \Psi(\tilde{B}_{e_{st}}^+),
\]

\[
\Psi(\beta) = \mu_{\beta}^+ + \nu_{\beta}^- \geq \min \min_{t,s} \{ \nu_{st}^+ \} + \max \max_{t,s} \{ \nu_{st}^- \} = \Psi(\tilde{B}_{e_{st}}^-).
\]

Now, there are three cases arise:

**Case 1.** If \( \Psi(\tilde{B}_{e_{st}}^-) < \Psi(\tilde{B}_{e_{st}}^+) \) and \( \Psi(\tilde{B}_{e_{st}}^-) > \Psi(\tilde{B}_{e_{st}}^-) \), then by comparison of two BFSNs, we have

\[
\tilde{B}_{e_{st}}^- \leq BFSWAA(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{emn}}) \leq \tilde{B}_{e_{st}}^+.
\]

**Case 2.** If \( \Psi(\tilde{B}_{e_{st}}^-) = \Psi(\tilde{B}_{e_{st}}^-) \), i.e., \( \mu_{\beta}^+ + \nu_{\beta}^- = \max \max_{t,s} \{ \nu_{st}^+ \} + \min \min_{t,s} \{ \nu_{st}^- \} \), then by above inequalities \( \mu_{\beta}^+ = \max \max_{t,s} \{ \nu_{st}^+ \} \) and \( \nu_{\beta}^- = \min \min_{t,s} \{ \nu_{st}^- \} \).

Therefore,

\[
\mathcal{H} = \mu_{\beta}^+ - \nu_{\beta}^- = \max \max_{t,s} \{ \nu_{st}^+ \} - \min \min_{t,s} \{ \nu_{st}^- \} = \mathcal{H}(\tilde{B}_{e_{st}}^+),
\]

then by comparison of two BFSNs, we have

\[
BFSWAA(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{emn}}) = \tilde{B}_{e_{st}}^+.
\]

**Case 3.** If \( \Psi(\tilde{B}_{e_{st}}^-) = \Psi(\tilde{B}_{e_{st}}^-) \), i.e., \( \mu_{\beta}^+ + \nu_{\beta}^- = \min \min_{t,s} \{ \nu_{st}^+ \} + \max \max_{t,s} \{ \nu_{st}^- \} \), then by above inequalities \( \mu_{\beta}^+ = \min \min_{t,s} \{ \nu_{st}^+ \} \) and \( \nu_{\beta}^- = \max \max_{t,s} \{ \nu_{st}^- \} \).

Hence,

\[
\mathcal{H} = \mu_{\beta}^+ - \nu_{\beta}^- = \min \min_{t,s} \{ \nu_{st}^+ \} - \max \max_{t,s} \{ \nu_{st}^- \} = \mathcal{H}(\tilde{B}_{e_{st}}^-),
\]

then by comparison of two BFSNs, we have

\[
BFSWAA(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{emn}}) = \tilde{B}_{e_{st}}^-.
\]

Thus, proof is completed.

**Theorem 3.8.** (Shift-invariance property) If \( \tilde{B}_e = \langle \mu^+, \nu^- \rangle \) be another BFSN, then

\[
BFSWAA(\tilde{B}_{e_{11}} \oplus \tilde{B}_e, \tilde{B}_{e_{12}} \oplus \tilde{B}_e, \ldots, \tilde{B}_{e_{emn}} \oplus \tilde{B}_e) = BFSWAA(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{emn}}) \oplus \tilde{B}_e.
\]

**Proof:** Since \( \tilde{B}_e \) and \( \tilde{B}_{e_{st}} \) are BFSNs. Then, we have \( \tilde{B}_e \oplus \tilde{B}_{e_{st}} = \langle 1 - (1 - \mu^+)(1 - \nu^-), -|\nu^-||\nu_{st}^-| \rangle \). Hence,

\[
BFSWAA(\tilde{B}_{e_{11}} \oplus \tilde{B}_e, \tilde{B}_{e_{12}} \oplus \tilde{B}_e, \ldots, \tilde{B}_{e_{emn}} \oplus \tilde{B}_e) = \bigoplus_{t=1}^{m} \phi_t \left( \bigoplus_{s=1}^{n} \theta_{s} \left( \tilde{B}_{e_{st}} \oplus \tilde{B}_e \right) \right)
\]

\[
= \left\langle 1 - \sum_{t=1}^{m} \left( \sum_{s=1}^{n} (1 - \mu_{st}^+) \theta_s (1 - \mu^+) \theta_t \right)^{\phi_t}, - \sum_{t=1}^{m} \left( \sum_{s=1}^{n} |\nu_{st}^-| \theta_s |\nu^-| \theta_t \right)^{\phi_t} \right\rangle
\]

\[
= \left\langle 1 - (1 - \mu^+) \sum_{t=1}^{m} \left( \sum_{s=1}^{n} (1 - \mu_{st}^+) \theta_s \right)^{\phi_t}, - \sum_{t=1}^{m} \left( \sum_{s=1}^{n} |\nu_{st}^-| \theta_s \right)^{\phi_t} \right\rangle \oplus \left\langle \mu^+, \nu^- \right\rangle
\]

Hence the result.
Theorem 3.9. (Homogeneity property) For any real number \( \lambda > 0 \), we have

\[
\text{BFSWA}(\lambda \tilde{B}_{e_{11}}, \lambda \tilde{B}_{e_{12}}, \ldots, \lambda \tilde{B}_{e_{mn}}) = \lambda \text{BFSWA}(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{mn}}).
\]

Proof: Let \( \tilde{B}_{e_{st}} = (\mu^+_{et}, \nu^-_{et}) \) \((s = 1, 2, \ldots, m; t = 1, 2, \ldots, n)\) be a collection of BFSNs and \( \lambda > 0 \) be any real number. Then, \( \lambda \tilde{B}_{e_{st}} = \left( 1 - (1 - \mu^+_{et})^\lambda, -|\nu^-_{et}|^\lambda \right) \). Thus,

\[
\begin{align*}
\text{BFSWA}(\lambda \tilde{B}_{e_{11}}, \lambda \tilde{B}_{e_{12}}, \ldots, \lambda \tilde{B}_{e_{mn}}) &= \left( 1 - \prod_{t=1}^{n} \left( \prod_{s=1}^{m} (1 - \mu^+_{et})^\lambda \theta_s \right)^{\phi_t}, -\prod_{t=1}^{n} \left( \prod_{s=1}^{m} |\nu^-_{et}|^\lambda \theta_s \right)^{\phi_t} \right) \\
&= \left( 1 - \left( \prod_{t=1}^{n} \left( \prod_{s=1}^{m} (1 - \mu^+_{et})^\theta_s \right)^{\phi_t} \right)^\lambda, -\left( \prod_{t=1}^{n} \left( \prod_{s=1}^{m} |\nu^-_{et}|^\theta_s \right)^{\phi_t} \right)^\lambda \right) \\
&= \lambda \text{BFSWA}(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{mn}}).
\end{align*}
\]

Hence the proof is completed. \( \square \)

3.2 Bipolar fuzzy soft weighted geometric averaging (BFSWGA) operator

To this section, we have defined bipolar fuzzy soft weighted geometric averaging (BFSWGA) operator for aggregating bipolar fuzzy soft input arguments.

Definition 3.10. Let \( \tilde{B}_{e_{st}} = (\mu^+_{et}, \nu^-_{et}) \) \((s = 1, 2, \ldots, m; t = 1, 2, \ldots, n)\) be a collection of BFSNs and \( \phi_t, \theta_s \) are the weight vectors for the parameter \( e_t \)'s and expert \( y_s \)'s respectively, satisfying \( \phi_t \geq 0, \theta_s \geq 0 \) such that\( \sum_{t=1}^{n} \phi_t = 1 \) and \( \sum_{s=1}^{n} \theta_s = 1 \). Then bipolar fuzzy soft weighted geometric (BFSWGA) operator is a function \( \text{BFSWGA} : \tilde{B}^n \rightarrow \tilde{B} \) such that

\[
\text{BFSWGA}(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{mn}}) = \bigotimes_{t=1}^{n} \left( \bigotimes_{s=1}^{m} \tilde{B}_{e_{st}}^{\phi_t} \right)^{\phi_t}.
\]

Theorem 3.11. Then bipolar fuzzy soft weighted geometric averaging (BFSWGA) operator is a function \( \text{BFSWGA} : \tilde{B}^n \rightarrow \tilde{B} \) such that

\[
\text{BFSWGA}(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{mn}}) = \left\langle \prod_{t=1}^{n} \left( \prod_{s=1}^{m} (\mu^+_{et})^{\phi_t}, -\prod_{t=1}^{n} \left( \prod_{s=1}^{m} (1 + \nu^-_{et})^{\theta_s} \right)^{\phi_t} \right), -1 + \prod_{t=1}^{n} \left( \prod_{s=1}^{m} (1 + \nu^-_{et})^{\theta_s} \right)^{\phi_t} \right\rangle.
\] (10)

Proof: For \( m = 1 \) and \( \theta_1 = 1 \) then by Definition 3.11, we have

\[
\text{BFSWGA}(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{mn}}) = \bigotimes_{t=1}^{n} \tilde{B}_{e_{st}}^{\phi_t} = \left\langle \prod_{t=1}^{n} (\mu^+_{et})^{\phi_t}, -\prod_{t=1}^{n} (1 + \nu^-_{et})^{\phi_t} \right\rangle.
\]

For \( n = 1 \) and \( \phi_1 = 1 \), then by Definition 3.11, we get

\[
\text{BFSWGA}(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{mn}}) = \bigotimes_{t=1}^{n} \tilde{B}_{e_{st}}^{\theta_t} = \left\langle \prod_{s=1}^{m} (\mu^+_{et})^{\theta_t}, -\prod_{s=1}^{m} (1 + \nu^-_{et})^{\theta_t} \right\rangle.
\]
Assume that (8) is true for \( n = p_1 + 1, m = p_2 \) and \( n = p_1, m = p_2 + 1 \), then it follows that
\[
\bigotimes_{t=1}^{p_1+1} \left( \bigotimes_{s=1}^{p_2} \tilde{B}_{est}^\theta \right)_{\phi_t} = \left( \prod_{t=1}^{p_1+1} \left( \prod_{s=1}^{p_2} (\mu_{st}^+ \theta_s)^{\phi_t} \right)_{\phi_t}, -1 + \prod_{t=1}^{p_1+1} \left( (1 + \nu_{st}^-)^{\theta_s} \right)_{\phi_t} \right).
\]

Also,
\[
\bigotimes_{t=1}^{p_1} \left( \bigotimes_{s=1}^{p_2+1} \tilde{B}_{est}^\theta \right)_{\phi_t} = \left( \prod_{t=1}^{p_1} \left( \prod_{s=1}^{p_2+1} (\mu_{st}^+ \theta_s)^{\phi_t} \right), -1 + \prod_{t=1}^{p_1} \left( (1 + \nu_{st}^-)^{\theta_s} \right)_{\phi_t} \right).
\]

Now for \( n = p_1 + 1 \) and \( m = p_2 + 1 \), we obtained
\[
\bigotimes_{t=1}^{p_1+1} \left( \bigotimes_{s=1}^{p_2+1} \tilde{B}_{est}^\theta \right)_{\phi_t} = \bigotimes_{t=1}^{p_1+1} \left( \bigotimes_{s=1}^{p_2} \tilde{B}_{est}^\theta \otimes \tilde{B}_{est}^\theta_{(p_2+1)t} \right)_{\phi_t}
\]
\[
= \left( \prod_{t=1}^{p_1+1} \left( \prod_{s=1}^{p_2} (\mu_{st}^+ \theta_s)^{\phi_t} \otimes \prod_{t=1}^{p_1+1} \left( (1 + \nu_{st}^-)^{\theta_s} \right)_{\phi_t} \right), -1 + \prod_{t=1}^{p_1+1} \left( (1 + \nu_{st}^-)^{\theta_s} \right)_{\phi_t} \right).
\]
Thus, (8) is true for \( n = p_1 + 1, m = p_2 + 1 \), therefore by induction the results hold for all \( n, m \geq 1 \).

Since, \( -1 \leq \nu_{st}^- \leq 0 \) \( \Leftrightarrow 0 \leq \prod_{s=1}^{m} (1 + \nu_{st}^-)^{\theta_s} \leq 1 \) \( \Leftrightarrow 0 \leq \prod_{t=1}^{n} \left( \prod_{s=1}^{m} (1 + \nu_{st}^-)^{\theta_s} \right)_{\phi_t} \leq 1 \) \( \Leftrightarrow -1 \leq -1 + \prod_{t=1}^{n} \left( \prod_{s=1}^{m} (1 + \nu_{st}^-)^{\theta_s} \right)_{\phi_t} \). On the other hand, \( 0 \leq \mu_{st}^+ \leq 1 \) \( \Leftrightarrow 0 \leq \prod_{t=1}^{n} (\mu_{st}^+ \theta_s)^{\phi_t} \leq 1 \) \( \Leftrightarrow 0 \leq \prod_{t=1}^{n} \left( \prod_{s=1}^{m} (\mu_{st}^+ \theta_s)^{\phi_t} \right) \leq 1 \). Therefore,
\[
-1 \leq -1 + \prod_{t=1}^{n} \left( \prod_{s=1}^{m} (1 + \nu_{st}^-)^{\theta_s} \right)_{\phi_t} + \prod_{t=1}^{n} \left( \prod_{s=1}^{m} (\mu_{st}^+ \theta_s)^{\phi_t} \right)_{\phi_t} \leq 1.
\]
Thus, aggregated value obtained by BFSWGA operator is again a BFSN.

**Example 3.12.** Let \( Y = \{y_1, y_2, y_3, y_4\} \) be the set of experts which are going to narrate the “attractiveness of two-wheeler bikes” under the set of parameters \( E = \{e_1 = \text{stylish}, e_2 = \text{weight}, e_3 = \text{milage}, e_4 = \text{price}\} \). The rating value of the experts is assumed to be given in the form of BFSNs \( (\mu_{st}^+, \nu_{st}^-)_{4 \times 3} \) for each parameters which are given in the following table.

<table>
<thead>
<tr>
<th>Experts</th>
<th>( e_1 )</th>
<th>( e_2 )</th>
<th>( e_3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( y_1 )</td>
<td>(0.6, -0.3)</td>
<td>(0.7, -0.2)</td>
<td>(0.4, -0.2)</td>
</tr>
<tr>
<td>( y_2 )</td>
<td>(0.5, -0.4)</td>
<td>(0.5, -0.3)</td>
<td>(0.8, -0.1)</td>
</tr>
<tr>
<td>( y_3 )</td>
<td>(0.4, -0.1)</td>
<td>(0.7, -0.1)</td>
<td>(0.5, -0.2)</td>
</tr>
<tr>
<td>( y_4 )</td>
<td>(0.6, -0.2)</td>
<td>(0.6, -0.3)</td>
<td>(0.6, -0.3)</td>
</tr>
</tbody>
</table>

Let \( \phi = (0.3, 0.2, 0.5)^T \) and \( \theta = (0.2, 0.1, 0.3, 0.4)^T \) be the weight vectors for the parameters and experts respectively. Then, we get by using Theorem 3.11 as:
\[
\text{BFSWG}(\tilde{B}_{e_{11}}, \tilde{B}_{e_{12}}, \ldots, \tilde{B}_{e_{42}}) = \left( \prod_{t=1}^{3} \left( \prod_{s=1}^{4} (\mu_{st}^+ \theta_s)^{\phi_t} \right)_{\phi_t}, -1 + \prod_{t=1}^{3} \left( \prod_{s=1}^{4} (1 + \nu_{st}^-)^{\theta_s} \right)_{\phi_t} \right).
\]
BFSWGA operator satisfies the following properties as similar as BFSWAA operator:

- **Idempotency Property**: If \( \tilde{B}_{e,s} = \tilde{B}_c = (\mu^+, \nu^-) \) for all \( s,t \), then \( \text{BFSWGA}(\tilde{B}_{e,11}, \tilde{B}_{e,12}, \ldots, \tilde{B}_{e,m_n}) = \tilde{B}_c \).

- **Boundedness Property**: If \( \tilde{B}_{e,s}^- = \langle \min \{\mu^+_{st}\}, \max \{\nu^-_{st}\} \rangle \) and \( \tilde{B}_{e,s}^+ = \langle \max \{\mu^+_{st}\}, \min \{\nu^-_{st}\} \rangle \), then \( \tilde{B}_{e,s}^- \leq \text{BFSWGA}(\tilde{B}_{e,11}, \tilde{B}_{e,12}, \ldots, \tilde{B}_{e,m_n}) \leq \tilde{B}_{e,s}^+ \).

- **Shift-invariance Property**: Let \( \tilde{B}_c = (\mu^+, \nu^-) \) be another BFSN, then \( \text{BFSWGA}(\tilde{B}_{e,11} \otimes \tilde{B}_c, \tilde{B}_{e,12} \otimes \tilde{B}_c, \ldots, \tilde{B}_{e,m_n} \otimes \tilde{B}_c) = \text{BFSWGA}(\tilde{B}_{e,11}, \tilde{B}_{e,12}, \ldots, \tilde{B}_{e,m_n}) \otimes \tilde{B}_c \).

- **Homogeneity Property**: For any real number \( \lambda > 0 \), we have \( \text{BFSWGA}(\tilde{B}^\lambda_{e,11}, \tilde{B}^\lambda_{e,12}, \ldots, \tilde{B}^\lambda_{e,m_n}) = \left( \text{BFSWGA}(\tilde{B}_{e,11}, \tilde{B}_{e,12}, \ldots, \tilde{B}_{e,m_n}) \right)^\lambda \).

### 4 Model for MCDM method using bipolar fuzzy information

In this section, we shall present MCDM using bipolar fuzzy soft weighted arithmetic averaging operator (BFSWAA) and bipolar fuzzy soft weighted geometric averaging (BFSWGA) operator in the environment of bipolar fuzzy soft numbers.

#### 4.1 An approach based on proposed operators

Let \( A = \{A_1, A_2, \ldots, A_l\} \) be the discrete set of alternatives which is evaluated by the set of \( m \) experts \( \{y_1, y_2, \ldots, y_m\} \) under the constraints of \( n \) parameters \( E = \{e_1, e_2, \ldots, e_n\} \). Let \( \theta = (\theta_1, \theta_2, \ldots, \theta_m)^T \) and \( \phi = (\phi_1, \phi_2, \ldots, \phi_n)^T \) are respectively denote the weight vectors of the \( m \) experts \( x_s \) and \( n \) parameters \( e_t \) such that \( \sum_{s=1}^m \theta_s = 1 \) and \( \theta_t > 0 \) for \( s \in [0, 1] \) such that \( \sum_{t=1}^n \phi_t = 1 \). In order to choose the best \( l \) alternates by the preference of \( n \) experts in the form of BFSNs \( \tilde{B}_{e,s} = (\mu^+_{st}, \nu^-_{st}) \) where \( -1 \leq \mu^+_{st} + \nu^-_{st} \leq 1 \) and collective over all decision matrix is expressed as \( M = \tilde{B}_{e,s} \). By these preference values of the experts, the aggregated BFSN \( \tilde{B}_{k} = (\mu^+_k, \nu^-_k) \) by applying weighted averaging or geometric averaging operators which is given in Eq. (5) and Eq. (8). Ranking order of the alternatives is determine based on the score function of the aggregated values of BFSNs \( \tilde{B}_{k} = (\mu^+_k, \nu^-_k, k = 1, 2, \ldots, l) \).

In the following algorithm, we propose to solve MCDM problem with bipolar fuzzy information using BFSWAA and BFSWGA operators.

**Step 1.** Collect all the information in the form of bipolar fuzzy soft matrix \( B = (\mu^+_{st}, \nu^-_{st}) \) (s = 1, 2, \ldots, m; t = 1, 2, \ldots, n) related to each alternatives under different parameters \( e_k = (1, 2, \ldots, l) \) as

\[
\tilde{B}_{m \times n} = M = \begin{bmatrix}
(\mu^+_{11}, \nu^-_{11}) & (\mu^+_{12}, \nu^-_{12}) & \cdots & (\mu^+_{1n}, \nu^-_{1n}) \\
(\mu^+_{21}, \nu^-_{21}) & (\mu^+_{22}, \nu^-_{22}) & \cdots & (\mu^+_{2n}, \nu^-_{2n}) \\
\vdots & \vdots & \ddots & \vdots \\
(\mu^+_{m1}, \nu^-_{m1}) & (\mu^+_{m2}, \nu^-_{m2}) & \cdots & (\mu^+_{mn}, \nu^-_{mn})
\end{bmatrix}
\]
The steps of the proposed approach performed and their corresponding details are reviewed as follows:

**Step 2.** To normalize the aggregated decision matrix by transforming values of benefit type (B) into cost (C) type by using the formula depicted in [15]:

\[ g_{ij} = \begin{cases} \bar{B}_{ij}^c, & \text{if } e_t \in \bar{B} \\ \bar{B}_{ij}^c, & \text{if } e_t \in \bar{C} \end{cases} \]

where \( \bar{B}_{ij}^c = (1 - \mu_{ij}^c, |\nu_{ij}^c| - 1) \) is the complement of \( \bar{B}_{ij} = (\mu_{ij}^c, \nu_{ij}^c) \).

**Step 3.** Aggregate the BFSNs \( \bar{B}_{ij}^c \) \((s = 1, 2, \ldots, m; t = 1, 2, \ldots, n)\) for each alternatives \( A_k \) \((k = 1, 2, \ldots, l)\) into collective decision matrix \( \Psi_k \) using BFSWAA or BFSWGA operators.

**Step 4.** Using Eq. (1) we get the score value of \( \Psi_k \) \((k = 1, 2, \ldots, l)\) for each alternatives \( A_k \) \((k = 1, 2, \ldots, l)\).

**Step 5.** Rank all the alternative \( A_k \) \((k = 1, 2, \ldots, l)\) in order to choose the best one(s) in accordance with \( \Psi_k \) \((k = 1, 2, \ldots, l)\).

**Step 6.** End.

5 Numerical example

In the above described decision-making method has been demonstrated with a practical example about the recruitment of a bank manager in a government of Indian banks. The panel for five experts, \( m_1, m_2, m_3, m_4, m_5 \) whose weight vector is \( \theta = (0.2, 0.15, 0.2, 0.3, 0.15)^T \), will give their judgement based on the performance of four candidates \( C_1, C_2, C_3, C_4 \) under the parameters \( E = \{ \text{computerknowledge}(e_1), \text{Decisiveness}(e_2), \text{Flexibility}(e_3), \text{Politeness}(e_4), \text{Hardworking}(e_5) \} \) with weight vector \( \phi = (0.2, 0.1, 0.3, 0.15, 0.25)^T \). Then, we utilize the developed method to get most desirable candidate(s).

5.1 By BFSWAA operator

The steps of the proposed approach performed and their corresponding details are reviewed as follows:

**Step 1.** The given candidates are being evaluated by five experts to give their grades in terms of BFSNs and are found in Tables 3, 4, 5, 6, respectively for each candidate.

**Step 2.** All the parameters are of same type, so, there is no required for normalization.

**Table 3:** Bipolar fuzzy soft matrix for the candidate \( C_1 \)

<table>
<thead>
<tr>
<th>Experts</th>
<th>( e_1 )</th>
<th>( e_2 )</th>
<th>( e_3 )</th>
<th>( e_4 )</th>
<th>( e_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( m_1 )</td>
<td>( (0.6, -0.2) )</td>
<td>( (0.5, -0.5) )</td>
<td>( (0.6, -0.3) )</td>
<td>( (0.3, -0.5) )</td>
<td>( (0.3, -0.4) )</td>
</tr>
<tr>
<td>( m_2 )</td>
<td>( (0.6, -0.4) )</td>
<td>( (0.3, -0.2) )</td>
<td>( (0.5, -0.4) )</td>
<td>( (0.4, -0.6) )</td>
<td>( (0.4, -0.1) )</td>
</tr>
<tr>
<td>( m_3 )</td>
<td>( (0.7, -0.1) )</td>
<td>( (0.4, -0.3) )</td>
<td>( (0.3, -0.1) )</td>
<td>( (0.7, -0.3) )</td>
<td>( (0.6, -0.2) )</td>
</tr>
<tr>
<td>( m_4 )</td>
<td>( (0.4, -0.5) )</td>
<td>( (0.7, -0.2) )</td>
<td>( (0.2, -0.6) )</td>
<td>( (0.6, -0.1) )</td>
<td>( (0.5, -0.1) )</td>
</tr>
<tr>
<td>( m_5 )</td>
<td>( (0.5, -0.2) )</td>
<td>( (0.6, -0.1) )</td>
<td>( (0.6, -0.2) )</td>
<td>( (0.4, -0.1) )</td>
<td>( (0.4, -0.2) )</td>
</tr>
</tbody>
</table>

**Table 4:** Bipolar fuzzy soft matrix for the candidate \( C_2 \)

<table>
<thead>
<tr>
<th>Experts</th>
<th>( e_1 )</th>
<th>( e_2 )</th>
<th>( e_3 )</th>
<th>( e_4 )</th>
<th>( e_5 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( m_1 )</td>
<td>( (0.3, -0.4) )</td>
<td>( (0.8, -0.1) )</td>
<td>( (0.7, -0.1) )</td>
<td>( (0.4, -0.1) )</td>
<td>( (0.2, -0.3) )</td>
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<tr>
<td>( m_2 )</td>
<td>( (0.5, -0.1) )</td>
<td>( (0.5, -0.2) )</td>
<td>( (0.4, -0.2) )</td>
<td>( (0.6, -0.1) )</td>
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<tr>
<td>( m_3 )</td>
<td>( (0.2, -0.1) )</td>
<td>( (0.4, -0.1) )</td>
<td>( (0.5, -0.4) )</td>
<td>( (0.4, -0.2) )</td>
<td>( (0.5, -0.2) )</td>
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<tr>
<td>( m_4 )</td>
<td>( (0.7, -0.2) )</td>
<td>( (0.5, -0.1) )</td>
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<td>( (0.3, -0.2) )</td>
<td>( (0.6, -0.4) )</td>
</tr>
</tbody>
</table>

**Step 3.** The opinion of experts for each candidate \( C_k \) \((k = 1, 2, 3, 4)\) are aggregated by using eq.(5) given as follows: \( \Delta_1 = (0.4918, -0.2326) \), \( \Delta_2 = (0.5154, -0.1700) \), \( \Delta_3 = (0.4800, -0.1656) \) and \( \Delta_4 = (0.4319, -0.1942) \).

**Step 4.** The values of score functions are: \( \Psi(\Delta_1) = 0.2592 \), \( \Psi(\Delta_2) = 0.3454 \), \( \Psi(\Delta_3) = 0.3144 \) and \( \Psi(\Delta_4) = 0.2377 \).
Step 5. Ranking all the candidates $C_k$ ($k = 1, 2, 3, 4$) in accordance with the value of the score functions $\Psi(\Delta_k)$ ($k = 1, 2, 3, 4$) of the overall bipolar fuzzy soft numbers as $C_2 \succ C_3 \succ C_4 \succ C_1$.

Step 6. Therefore, $C_2$ is the most desirable candidate for the post.

5.2 By using BFSWGA operator

If we apply BFSWGA operator on the proposed problem for the selection of appropriate candidate(s) that follows the following steps:

Step 3. The aggregated values for each candidates $C_k$ ($k = 1, 2, 3, 4$) using BFSWGA operator are follows from Eq. (10):

$$\Delta_1 = (0.4432, -0.3084), \Delta_2 = (0.4515, -0.1999), \Delta_3 = (0.4224, -0.1825) \text{ and } \Delta_4 = (0.3960, -0.2204).$$

Step 4. The values of score functions are: $\Psi(\Delta_1) = 0.1384, \Psi(\Delta_2) = 0.2516, \Psi(\Delta_3) = 0.2399$ and $\Psi(\Delta_4) = 0.1756$.

Step 5. Ranking all the candidates $C_k$ ($k = 1, 2, 3, 4$) in accordance with the value of the score functions $\Psi(\Delta_k)$ ($k = 1, 2, 3, 4$) of the overall bipolar fuzzy soft numbers as $C_2 \succ C_3 \succ C_4 \succ C_1$.

Step 6. Hence, $C_2$ is the most appropriate candidate for the post.

From the above analysis, it is clear that although overall rating values of the alternatives are different by using two operators, but ranking order of the alternatives are similar, the most desirable alternative is $C_2$.

<table>
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<th>$e_1$</th>
<th>$e_2$</th>
<th>$e_3$</th>
<th>$e_4$</th>
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<tr>
<td>$m_5$</td>
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<td>(0.5, -0.4)</td>
<td>(0.4, -0.1)</td>
<td>(0.4, -0.1)</td>
<td>(0.7, -0.2)</td>
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Table 6: Bipolar fuzzy soft matrix for the candidate $C_4$
6 Comparative analysis

To compare the proposed work with the existing approach, an analysis has been made based on aggregation operator (See, [42]). In that reason, the different parameters of bipolar fuzzy soft numbers are aggregated by using weighted averaging operator corresponding to the weighted vector \((0.2, 0.1, 0.3, 0.15, 0.25)^T\) and then obtained aggregated bipolar fuzzy soft matrix for the different candidates \(C_k (k = 1, 2, 3, 4)\) given in Table 7. From this evaluated matrix, a comparative study has been established with the only existing work based on Hamacher aggregation operator on bipolar fuzzy numbers, developed by Wei et al. [42] for each candidate are shown in Table 8. From this table, we have seen that the candidate \(C_2\) is most appropriate for the selected post. The method of this propose paper utilize advance technique to compare the existing works [1, 51] where a decision-making method has been develop based on some soft algebraic operations in bipolar fuzzy soft environment but present paper contains a decision-making method based on aggregating bipolar fuzzy soft arguments in the environment of bipolar fuzzy soft numbers. The advantages of this paper is that they are capable to facilitate the descriptions of the real-world problems situation with the help of their parameterizations property. Therefore, proposed method can be utilized to solve decision problems instead of other existing operator in the environment of bipolar soft set.

7 Conclusions

In this article, we have studied multi-criteria decision-making problem using in the environment of bipolar fuzzy soft information. We have introduced two new operators namely BFSWAA and BFSWGA operators in bipolar fuzzy soft environment. The different feature of those recommend operators is deliberated. For this purpose, firstly some algebraic structures of two BFSNs and their operational rules and aggregation operators have been proposed. Some properties of these two kinds of operators have been established. A decision-making problems has been studied based on BFSWAA and BFSWGA operators under the environment of bipolar fuzzy soft information. The main advantage of these operators is that they are able to make smooth description of the real-world problems by the use of parameterizations factor. Ultimately, a realistic instance for the selection of best candidate for a post of bank’s manager is provided to develop a strategy and in accordance with expounding the utility then effectiveness about the proposed method. In future, the application of our proposed model can be applied in decision-making theory, risk evaluation and other domains under different uncertain environments.

Acknowledgement

We would like to thank the anonymous reviewers for their insightful and constructive comments and suggestions that have been helpful for providing a better version of the present work.

References


A robust aggregation operators for multi-criteria decision-making method with bipolar fuzzy soft environment


