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Research Article

A Novel Enhanced Supplier Selection Method Used for Handling Hesitant Fuzzy Linguistic Information

Kuei-Hu Chang [1,2]

[1]Department of Management Sciences, R.O.C. Military Academy, No. 1, Wei-Wu Rd., Fengshan Dist, Kaohsiung 830, Taiwan
[2]Institute of Innovation and Circular Economy, Asia University, Taichung 413, Taiwan

Correspondence should be addressed to Kuei-Hu Chang; evenken2002@gmail.com

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Today's competitive businesses have been shifted from the company-to-company competition model to the supply chain-to-supply chain competition model. The selection of the most suitable supplier determines customer satisfaction and enterprise competitive advantage. However, the typical supplier selection approaches did not consider the ordered weights between the evaluations of attribute values, resulting in distorted assessment result. Moreover, experts often uncertainly decide the exact value of the evaluation attribute's rating, have linguistic term sets equivocation, or give ambiguous information, which increase the difficulty of the supplier evaluation process. To deal with the aforementioned problem, we have proposed a novel enhanced supplier selection method for handling hesitant fuzzy linguistic information. To verify the approach, by taking network security system assessment as an example to explain the use of the proposed novel enhanced supplier selection method, the calculation result is compared with the result of the arithmetic average and symbolic methods. The results show that the proposed novel enhanced supplier selection method is more accurate and reasonable and can better reflect real situations.

1. Introduction

During the advanced information era, competition has shifted from a traditional model of company-versus-company competition to that between supply chains. Adopting the most appropriate suppliers ensures the customer satisfaction and competitiveness of the entire supply chain. Thus, the supplier selection process is especially crucial in the entire supply chain management operation. Supplier selection includes quantitative and qualitative criteria and is classified as a complex multiple attribute decision (MADM) issue. In the process of supplier selection, traditional calculation methods require that the attribute values of possible alternatives be precise. However, in many practical circumstances, the attribute values of possible alternatives include linguistic and equivocal information. Traditional calculation methods cannot effectively address complex MADM problems with fuzzy or ambiguous information. The fuzzy-set-based methods and data envelopment analysis are commonly used approaches to solve complex MADM problems, such as [1]. Thus, many authors used a fuzzy-set-based approach to handle supply-chain-related issues under fuzzy information environments [2–5].

Herrera and Martinez [6] developed the 2-tuple linguistic representation model (2-tuple LRD) to prevent information loss and distortion for computing words of natural languages. This model is constructed by a pair of values: the information linguistic label center and the symbolic translation value. There is extensive research on the 2-tuple LRD. For example, Liu et al. [7] combined interval 2-tuple linguistic variables and the VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method to overcome problems of personnel selection that exist in the group decision-making issues. Based on the 2-tuple LRD, Wan [8] introduced an extended 2-tuple hybrid linguistic weighted arithmetic average to effectively handle the problems of personnel selection for MADM issues. Based on the Choquet integral, Beg and Rashid [9] introduced new interval-valued aggregation operators that related to 2-tuple linguistic information to process interval-valued 2-tuple linguistic information. This 2-tuple LRD has been utilized in various disciplines, for instance, supplier selection [10–12], customer collaborative product innovation design [13], computer network security systems [14], semiconductor manufacturing [15], robot selection [16], military simulation training systems [17], and photovoltaic cell manufacturing process [18].

Another shortcoming of traditional calculation methods is that it does not consider the ranking weight of the evaluation attribute value when dealing with issues related to supplier selection. The ordered weight is a crucial factor in MADM problems and preference ranking [19, 20]. Yager [21] firstly introduced the ordered weighted average (OWA) operator to provide a family of parameterized aggregation operators between the maximum and the minimum operators. Work on OWA operators and their application has progressed rapidly. For instance, Yari and Chaji [22] used M-entropy measures to determine the weights of the OWA operator. Based on an optimal deviation mode, Zhou and Chen [23] extended the OWA operator to generalize ordered weighted logarithm aggregation operators for handling group decision-making issues. For handling the multi-attribute group decision-making issues, Wan and Dong [24] developed 4 types of power geometric operators for trapezoidal intuitionistic fuzzy numbers: the power geometric operator, power hybrid geometric operator, power-weighted geometric operator, and power-ordered weighted geometric operator. At present, the OWA operator has widely been utilized, such as target recognition system [25], fighter aircraft airborne radar systems [26], supplier selection [27], thin-film transistor liquid crystal display manufacturing [28], and personnel selection [29]. How to determine the weight of OWA operators is a very critical issue in MADM problems. For a given level of orness, O'Hagan [30] firstly introduced the maximal entropy concept to determine the OWA operators' weights. Extending this concept, Fuller and Majlender [31] derived a polynomial equation based on Lagrange multipliers to determine the optimal weighting vector under maximal entropy. Fuller and Majlender [32] used Kuhn-Tucker second-order sufficiency conditions to determine OWA operator weights; in addition, it was named as a minimal variance OWA (MVOWA) weighting method.

In cases of fuzzy or ambiguous information, experts are unable to determine the exact numerical values of the evaluation data. To manage such information, Torra [33] introduced hesitant fuzzy sets (HFS) and demonstrated that the envelope of HFS is an intuitionistic fuzzy set. Extending HFS to qualitative decision-making problems, Rodriguez et al. [34] firstly proposed hesitant fuzzy linguistic term sets (HFLTSs) to address hesitant linguistic decision-making issues. In the selection and assessment of suppliers, experts are usually hesitant about linguistic term sets (LTSs) in representing the values of evaluated data. For equivocal information, traditional calculation methods are deleted from uncertain information systems, causing information to become distorted and lost in the supplier selection process. Thus, to solve these shortcomings, this study integrates the MVOWA and HFLTS to strengthen the evaluation of supplier selection.

The major contributions of this paper include three innovative points. Firstly, the proposed novel enhanced supplier selection method can effectively handle linguistic information during the information aggregation process. Secondly, the proposed method considers the ordered weight of assessment attribute values and uses MVOWA weights to aggregate the evaluation values of the evaluation attributes in the supplier selection issues. Finally, the proposed method uses the HFLTS to deal with ambiguous information, which can handle hesitant information more flexibly.

The rest of this paper is arranged as follows: Section 2 reviews the research on this topic, including the minimal variability OWA (MVOWA) operator, HFLTS, and 2-tuple LRD. Section 3 introduces the proposed method, which combines the MVOWA and HFLTS for supplier selection problems. In Section 4, an example of network security system selection in the military is illustrated, and the comparisons of the calculated results between other methods are also illustrated. The final section gives the conclusions.

2. Related Works

2.1. MVOWA Operator. The OWA operator was proposed by Yager [21] which is an aggregation operator between the maximum operator and minimum operator, which is defined as follows.

Definition 1 (see [21]). The OWA operator of dimensional n is a mapping OWA: $R^n \longrightarrow R$ that has a correlative weight vector $w = (w_1, w_2, \ldots, w_n)$, such that $w_i \in [0,1]$ and $\sum_{i=1}^{n} w_i = 1$, shown as the following formula:

$$OWA(a_1, a_2, \ldots, a_n) = \sum_{i=1}^{n} w_i b_i, \tag{1}$$

where b_i is the ith largest element in the aggregated objects $(a_1, a_2, \ldots, a_n)$ collection.

Fuller and Majlender [32] used the sufficiency conditions of Kuhn-Tucker second-order to obtain the minimal variability weighting vector of any level of *orness*, named as MVOWA operator weights. The computing process of the MVOWA operator weights is shown as follows:

$$\begin{aligned} \text{Minimizing } Var(w) &= \sum_{i=1}^{n} 1/n\left(w_i - E(w)\right)^2 \\ &= 1/n\sum_{i=1}^{n} w_i^2 - \left(1/n\sum_{i=1}^{n} w_i\right)^2 \\ &= 1/n\sum_{i=1}^{n} w_i^2 - 1/n^2 \\ \text{Subject to } \alpha &= 1/n-1\sum_{i=1}^{n}(n-i)w_i, 0 \le \alpha \le 1, \\ \sum_{i=1}^{n} w_i = 1, &\qquad w_i \in [0,1], \qquad i = 1, \ldots, n. \end{aligned} \tag{2}$$

For any $\alpha \in [0,1]$, assume that l always exists, the associated weighting vectors are obtained as

$w_j^* = 0$ if $j \notin I_{\{l,n\}}$,

$$w_n^* = \frac{6(n-1)(1-\alpha) - 2(n+2l-4)}{(n-l+1)(n-l+2)}, \tag{3}$$

$$w_l^* = \frac{2(2n+l-2) - 6(n-1)(1-\alpha)}{(n-l+1)(n-l+2)}, \tag{4}$$

$$w_j^* = \frac{j-l}{n-l} w_n + \frac{n-j}{n-l} w_l \text{ if } j \in I_{\{l+1,n+1\}}, \tag{5}$$

where α is the situation parameter, n is the number of attributes, and w is a weight vector.

2.2. HFLTS. According to the linguistic approach and HFS, Rodriguez et al. [34] proposed HFLTSs to handle multicriteria linguistic decision-making issues. The definitions are shown as follows.

Definition 2 (see [34, 35]). HFLTS H_s is an ordered finite subset of the S continuous linguistic terms, where $S = \{s_0, s_1, \ldots, s_g\}$ is a LTS.

Definition 3 (see [34, 35]). Assumed S be a LTS, $S = \{s_0, s_1, \ldots, s_g\}$, and H_s be a HFLTS. The complement set H_s^c is defined as follows:

$$H_s^c = S - H_s = \{s_i | s_i \in S \text{ and } s_i \notin H_s\}. \tag{6}$$

Definition 4 (see [34, 35]). The intersection and union between 2 arbitrary HFLTSs, H_s^1 and H_s^2, are defined as follows:

$$\begin{aligned} H_s^1 \cap H_s^2 &= \{s_i | s_i \in H_s^1 \text{ and } s_i \in H_s^2\}, \\ H_s^1 \cup H_s^2 &= \{s_i | s_i \in H_s^1 \text{ or } s_i \in H_s^2\}, \end{aligned} \tag{7}$$

where the result is a HFLTS.

Definition 5 (see [34, 35]). Assumed S be a LTS, $S = \{s_0, s_1, \ldots, s_g\}$, and let H_s be an arbitrary HFLTS. The lower bound H_{s^-} and the upper bound H_{s^+} of the HFLTS H_s are defined as follows:

$$\begin{aligned} H_{S^-} &= \min(s_i) = s_j, s_i \in H_S \text{ and } s_i \geq s_j \forall i, \\ H_{S^+} &= \max(s_i) = s_j, s_i \in H_S \text{ and } s_i \leq s_j \forall i. \end{aligned} \tag{8}$$

Definition 6 (see [34, 36]). The envelope of the HFLTS, $env(H_s)$, is a linguistic interval, and the limits are obtained through its upper bound and its lower bound.

$$env(H_s) = [H_{s^-}, H_{s^+}], H_{s^-} \leq H_{s^+} \tag{9}$$

Example 1. Let $S = \left\{ \begin{array}{c} S0 = \text{extremely bad (EB)}, \\ S1 = \text{very bad (VB)}, \\ S2 = \text{bad (B)}, \\ S3 = \text{medium (M)}, \\ S4 = \text{good (G)}, \\ S5 = \text{very good (VG)}, \\ S6 = \text{extremely good (EG)} \end{array} \right\}$ be a LTS and $H_s = \{S4, S5, S6\}$ be a HFLTS of S; its envelope is

$$\begin{aligned} H_{s^-}(S4, S5, S6) &= S4, \\ H_{s^+}(S4, S5, S6) &= S6, \\ env(H_s) &= [S4, S6]. \end{aligned} \tag{10}$$

2.3. 2-Tuple LRD. To extend the symbolic translation concept, Herrera and Martinez [6] introduced the 2-tuple LRD. This method uses the linguistic 2-tuple (s_i, α) to represent the linguistic information, where the semantic element s_i is evaluated by the linguistic variable S, defined in the LTS $S = \{s_0, s_1, \ldots, s_g\}$ and $i \in [0, g]$. α is a numerical value representing symbol translation.

Definition 7 (see [6, 37]). Suppose $\beta \in [0, g]$ be the aggregated results of a set of label indexes are evaluated in a LTS $S = \{s_0, s_1, \ldots, s_g\}$. Assume $i = \text{round}(\beta)$ and $\alpha = \beta - i$ be two values, such that $\alpha \in [-0.5, 0.5)$ and $i \in [0, g]$; then, α is called a translation of symbolic, with round being the usual round operation.

Definition 8 (see [6, 38]). Suppose $S = \{s_0, s_1, \ldots, s_g\}$ be a LTS and $\beta \in [0, g]$ be a value that supports the symbolic aggregation operation result. The function Δ for obtaining the 2-tuple linguistic information that equals to β is defined as follows:

$$\begin{gathered} \Delta\colon [0, g] \longrightarrow S \times [-0.5, 0.5), \\ \Delta(\beta) = (s_i, \alpha), \text{with} \begin{cases} s_i, & i = \text{round}(\beta) \\ \alpha = \beta - i, & \alpha \in [-0.5, 0.5) \end{cases}, \end{gathered} \tag{11}$$

where α is called a translation of symbolic, s_i has the closest index label to β, and round is the usual round operation.

Definition 9 (see [6, 10]). Suppose $x = \{(s_1, \alpha_1), (s_2, \alpha_2), \ldots, (s_n, \alpha_n)\}$ be a 2-tuple set and $w = (w_1, w_2, \ldots, w_n)$ be their associated weights, with $i = 1, 2, \ldots, n$, $w_i \in [0, 1]$, $\sum_{i=1}^n w_i = 1$. The 2-tuple weighted average (2-tuple WA) operator is defined as

$$2\,\text{tuple WA}(X) = n\left(\frac{1}{n}\sum_{i=1}^{n} w_i \Delta^{-1}(s_i, \alpha_i)\right) = \Delta\left(\frac{1}{n}\sum_{i=1}^{n} w_i \beta_i\right). \tag{12}$$

Definition 10 (see [6, 38]). Suppose (s_u, α_1) and (sv, α_2) be two 2 tuples. The 2-tuple linguistic information is compared per an ordinary lexicographic order.

(1) If $u > v$, then $(s_k, \alpha_1) > (s_l, \alpha_2)$.

(2) If $u = v$, then

  (a) If $\alpha_1 > \alpha_2$, then $(s_k, \alpha_1) > (s_l, \alpha_2)$
  (b) If $\alpha_1 = \alpha_2$, then $(s_k, \alpha_1) = (s_l, \alpha_2)$
  (c) If $\alpha_1 < \alpha_2$, then $(s_k, \alpha_1) < (s_l, \alpha_2)$.

(3) If $u < v$, then $(s_k, \alpha_1) < (s_l, \alpha_2)$.

3. Proposed Integration of HFLTS and the MVOWA

With the advent of the information age, the supply chain-versus-supply chain is becoming the new mode of competition instead of the company versus company. The appropriate suppliers must be selected to ensure the customer satisfaction and competitiveness of the entire supply chain. Attributing rating values judgments that are made by experts are usually expressed as LTSs in supplier selection. Then, many authors used LTSs to handle supply-chain-related issues [2, 5, 39–41]. However, the experts are often hesitant between several assessment values when assessing attribute rating values, which increases the complexity and difficulty of supplier selection. Moreover, most studies did not consider the ordered weight of the evaluation attribute rating values in the supplier selection problems (such as [42–44]), which may cause that biased results. Ordered weight is one of several important factors that are used in multiple-attribute decision-making (MADM) and preference ranking [19, 20]. To solve this problem, this study integrates the HFLTS and MVOWA to strengthen the evaluation of supplier selection. The flow diagram of the proposed novel enhanced supplier selection method is shown in Figure 1.

The proposed novel enhanced supplier selection method embraces 7 steps as follows.

Step 1. Determine the possible alternatives and assessment attributes.

Take all of the experts' opinions into account to determine the possible alternatives and assessment attributes.

Step 2. Determine the assessment attributes weights.

Summarize the opinions of the team's experts to obtain the assessment attribute weights.

Step 3. Determine the attribute rating values for possible alternatives.

Based on the team's experts' knowledge and experience, experts use the LTS S to individually determine the attribute rating values.

Step 4. Perform defuzzification.

Apply centroid defuzzification to calculate crisp values. The defuzzified centroid ($C_{\tilde{X}}$) of the fuzzy number $\tilde{X} = (a, b)$ can be calculated by the following formula [45, 46].

$$C_{\tilde{X}} = \frac{(a, b)}{2}, \tag{13}$$

where b is the right boundary and a is the left boundary.

Step 5. Compute the MVOWA weights.

Use equations (3)–(5) to compute the MVOWA weights.

Step 6. Using MVOWA weights to compute the aggregated value.

Based on Step 4 and Step 5, use (1) to compute the aggregated evaluation values of the alternative using MVOWA weights.

Step 7. Analyze the calculation results, and select the best alternative.

Based on the calculation results of Step 6, rank the alternative order according to the aggregated evaluation values of the alternative.

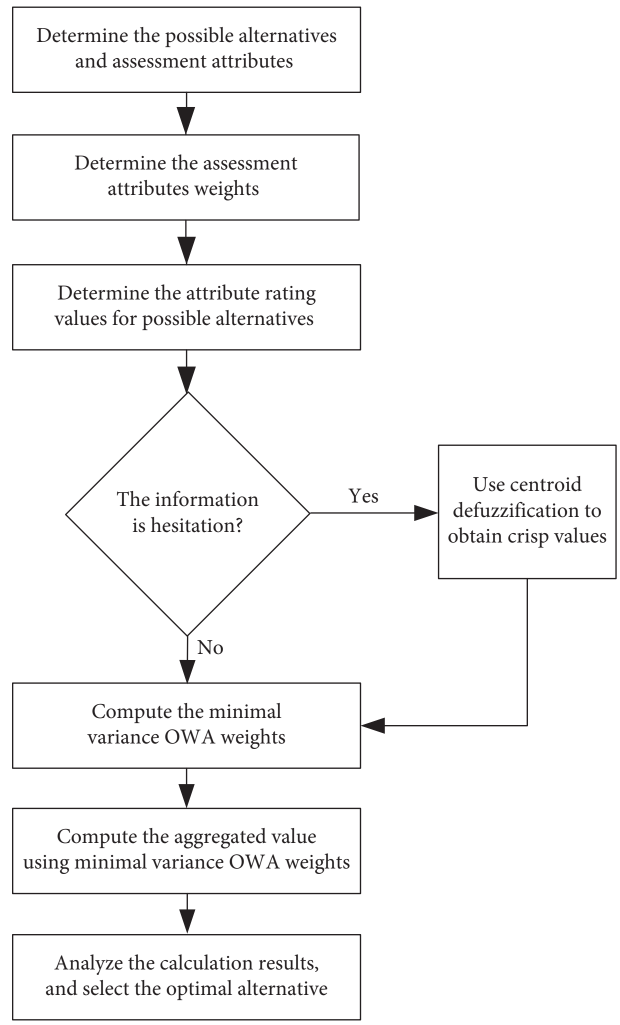

Figure 1: Flow diagram of the proposed novel enhanced supplier selection method.

4. Case Study

This study uses an illustrative example of selecting a network security system in the military from Zhang [14] to demonstrate the proposed procedure. After a preliminary screen, the network security system considers 4 alternatives, A_i ($i = 1, 2, 3, 4$), for further evaluation. The team of experts must make a decision according to the 5 following assessment attributes: tactics ($G1$), technology ($G2$), economy ($G3$), logistics ($G4$), and strategy ($G5$). The 4 possible alternatives are evaluated using the linguistic information per the LTS S. S can be defined as

$$\begin{aligned} S = \{&S0 = \text{extremely bad (EB)}, S1 = \text{very bad (VB)},\\ &S2 = \text{bad (B)}, S3 = \text{medium (M)}, \quad S4 = \text{good (G)},\\ &S5 = \text{very good (VG)}, S6 = \text{extremely good (EG)}\}. \end{aligned} \tag{14}$$

The network security system selection team comprises 3 decision-makers, each of whom evaluates the attributes rating values for the 4 alternatives according to the LTS S, as shown in Table 1. The weight vector of the attributes is $w = [0.10, 0.15, 0.20, 0.30, 0.25]$.

4.1. Solution Based on the Typical Arithmetic Average Method. Although the mathematical operation of the typical arithmetic average method is simpler, it requires that all of the data be certain. In part, the attribute values that were provided by expert P3 were ambiguous. Therefore, typical arithmetic average method only considered the certain information that were provided by experts P1 and P2. The rating values of the network security system selection by the typical arithmetic average method are shown in Table 2.

Now, the ranking of the alternatives is Alternative 1 ≻ Alternative 4 ≻ Alternative 3 ≻ Alternative 2.

Thus, the most suitable alternative is Alternative 1.

4.2. Solution Based on the Symbolic Method [6, 47]. Delgado et al. [47] firstly defined the symbolic method. This method aggregated linguistic variables in a convex combination to correspond to the linguistic terms. However, this method cannot handle situations in which experts equivocate with regard to their preferences for objects in supplier selection. In this case, partially data from expert P3 were ambiguous. Therefore, only considered the certain information that were provided by experts P1 and P2. The aggregate evaluation values of the network security system by the symbolic method are shown in Table 3.

This section uses the assessment attribute $G1$ and the aggregated evaluation value for alternative 1 which is $S4$ in this illustrative example; the computation process is as follows:

$$\begin{aligned}
&C^2\left\{\left(\frac{1}{2}, S5\right), \left(\frac{1}{2}, S3\right)\right\} \\
&= \left(\frac{1}{2} \otimes S5\right) \oplus \left(1 - \frac{1}{2}\right) \otimes (S3) = Sk, \\
&k = \min\{6,\ 3 + \operatorname{round}(0.5n(5-3))\} = 4, \\
&\Rightarrow C^2\left\{\left(\frac{1}{2}, S5\right), \left(\frac{1}{2}, S3\right)\right\} = S4.
\end{aligned} \tag{15}$$

This section uses an aggregate rating value of $S4$ for alternative 1 in this illustrative example; the computing process is as follows:

$$\begin{aligned}
C^5&\{(0.10, S4), (0.15, S5), (0.20, S3), (0.30, S5), (0.25, S4)\} \\
&= (0.10 \otimes S4) \oplus (1 - 0.10) \\
&\otimes C^4\{(0.167, S5), (0.222, S3), (0.333, S5), (0.278, S4)\}, \\
C^4&\{(0.167, S5), (0.222, S3), (0.333, S5), (0.278, S4)\} \\
&= (0.167 \otimes S5) \oplus (1 - 0.167), \\
&\otimes C^3\{(0.267, S3), (0.4, S5), (0.333, S4)\}, \\
C^3&\{(0.267, S3), (0.4, S5), (0.333, S4)\} \\
&= (0.267 \otimes S3) \oplus (1 - 0.267) \otimes C^2\{(0.545, S5), (0.455, S4)\}, \\
C^2&\{(0.545, S5), (0.455, S4)\} = (0.545 \otimes S5) \oplus (1 - 0.545) \otimes S4 = Sk, \\
k &= \min\{6,\ 4 + \operatorname{round}(0.545n(5-4))\} = 5, \\
&\Rightarrow C^2\{(0.545, S5), (0.455, S4)\} = S5, \\
C^3&\{(0.267, S3), (0.4, S5), (0.333, S4)\} = (0.267 \otimes S3) \oplus (1 - 0.267) \otimes S5, \\
k &= \min\{6,\ 3 + \operatorname{round}(0.267n(5-3))\} = 4, \\
&\Rightarrow C^3\{(0.267, S3), (0.4, S5), (0.333, S4)\} = S4, \\
C^4&\{(0.167, S5), (0.222, S3), (0.333, S5), (0.278, S4)\} \\
&= (0.167 \otimes S5) \oplus (1 - 0.167) \otimes S4, \\
k &= \min\{6,\ 4 + \operatorname{round}(0.167n(5-4))\} = 4, \\
&\Rightarrow C^4\{(0.167, S5), (0.222, S3), (0.333, S5), (0.278, S4)\} = S4, \\
C^5&\{(0.10, S4), (0.15, S5), (0.20, S3), (0.30, S5), (0.25, S4)\} \\
&= (0.10 \otimes S4) \oplus (1 - 0.10) \otimes S4, \\
k &= \min\{6,\ 4 + \operatorname{round}(0.10n(4-4))\} = 4 \\
&\Rightarrow C^5\{(0.10, S4), (0.15, S5), (0.20, S3), (0.30, S5), (0.25, S4)\} = S4.
\end{aligned} \tag{16}$$

Table 1: Attribute rating values for four alternatives.

Attribute		G1	G2	G3	G4	G5
Alternative 1	P1	S5	S6	S3	S4	S6
	P2	S3	S4	S2	S6	S2
	P3	S1	S5	S6	S5	S4
Alternative 2	P1	S3	S1	S2	S1	S0
	P2	S6	S6	S5	S3	S1
	P3	S2	S4	S1	S4	S3
Alternative 3	P1	S4	S0	S6	S3	S2
	P2	S2	S3	S6	S1	S3
	P3	[S4, S5]	S2	S5	[S1, S2]	S6
Alternative 4	P1	S1	S5	S3	S2	S3
	P2	S1	S0	S4	S4	S6
	P3	[S5, S6]	S1	S0	[S4, S6]	S2

Table 2: Network security system selection by the typical arithmetic average method.

	Alternative 1	Alternative 2	Alternative 3	Alternative 4
Rating values	S4.15	S2.4	S2.95	S3.2

Table 3: Aggregate evaluation values of the network security system by the symbolic method.

Attribute	G1	G2	G3	G4	G5	Aggregate rating values
Alternative 1	S4	S5	S3	S5	S4	S4
Alternative 2	S5	S4	S4	S2	S1	S3
Alternative 3	S3	S2	S6	S2	S3	S3
Alternative 4	S1	S3	S4	S3	S5	S4

4.3. Solution Based on the Proposed Novel Enhanced Supplier Selection Method. The proposed novel enhanced supplier selection method integrates the MVOWA and HFLTS to strengthen the evaluation of supplier selection, based on Steps 1 to 7 (Section 3). First, experts come together to discuss the selection of a network security system, including 4 possible alternatives and 5 assessment attributes (Step 1). Then, calculate the aggregated value of the experts' opinions and the assessment attributes weights ($w = [0.10, 0.15, 0.20, 0.30, 0.25]$) (Step 2). Moreover, the attribute rating values for the alternatives are determined per the experts' knowledge and experience (see Table 1) (Step 3). The remaining steps are described as follows:

Step 4 (defuzzification). This paper used the centroid defuzzification method to calculate crisp values. According to equation (9), the defuzzification attribute rating values for the 4 alternatives are calculated (see Table 4).

Step 5 (compute the MVOWA weights). Based on equations (3)–(5), the MVOWA weights are computed for $n = 5$, as shown in Table 5.

For example, when $n = 5$ and $\alpha = 0.7$, by equation (3), it is found that

Table 4: Defuzzification of attribute rating values for the four alternatives.

Attribute		G1	G2	G3	G4	G5
Alternative 1	P1	S5	S6	S3	S4	S6
	P2	S3	S4	S2	S6	S2
	P3	S1	S5	S6	S5	S4
Alternative 2	P1	S3	S1	S2	S1	S0
	P2	S6	S6	S5	S3	S1
	P3	S2	S4	S1	S4	S3
Alternative 3	P1	S4	S0	S6	S3	S2
	P2	S2	S3	S6	S1	S3
	P3	S4.5	S2	S5	S1.5	S6
Alternative 4	P1	S1	S5	S3	S2	S3
	P2	S1	S0	S4	S4	S6
	P3	S5.5	S1	S0	S5	S2

Table 5: MVOWA weights when $n = 5$.

Alpha	Weight				
	w1	w2	w3	w4	w5
0	0.000	0.000	0.000	0.000	1.000
0.1	0.000	0.000	0.033	0.333	0.633
0.2	0.000	0.040	0.180	0.320	0.460
0.3	0.040	0.120	0.200	0.280	0.360
0.4	0.120	0.160	0.200	0.240	0.280
0.5	0.200	0.200	0.200	0.200	0.200
0.6	0.280	0.240	0.200	0.160	0.120
0.7	0.360	0.280	0.200	0.120	0.040
0.8	0.460	0.320	0.180	0.040	0.000
0.9	0.633	0.333	0.033	0.000	0.000
1	1.000	0.000	0.000	0.000	0.000

$$w_5 = \frac{6(n-1)(1-\alpha) - 2(n+2l-4)}{(n-l+1)(n-l+2)} = \frac{6(5-1)(1-0.7) - 2(5+2-4)}{(5-1+1)(5-1+2)} = 0.040. \tag{17}$$

By (4), it is found that

$$w_1 = \frac{2(2n+l-2) - 6(n-1)(1-\alpha)}{(n-l+1)(n-l+2)} = \frac{2(2\times 5+1-2) - 6(5-1)(1-0.7)}{(5-1+1)(5-1+2)} = 0.360. \tag{18}$$

Therefore, by (5), it is found that

$$\begin{aligned} w_2 &= \frac{n-j}{n-l}w_l + \frac{j-l}{n-l}w_n = \frac{5-2}{5-1}w_1 + \frac{2-1}{5-1}w_5 = 0.280, \\ w_3 &= \frac{n-j}{n-l}w_l + \frac{j-l}{n-l}w_n = \frac{5-3}{5-1}w_1 + \frac{3-1}{5-1}w_5 = 0.200, \\ w_4 &= \frac{n-j}{n-l}w_l + \frac{j-l}{n-l}w_n = \frac{5-4}{5-1}w_1 + \frac{4-1}{5-1}w_5 = 0.120. \end{aligned} \tag{19}$$

Step 6 (using MVOWA weights to compute the aggregated value). Based on Table 4, Table 5, and equation (1), the

Table 6: Summarized evaluation values of the network security system by the proposed method.

	Alternative 1	Alternative 2	Alternative 3	Alternative 4
$\alpha = 0.5$	0.857	0.517	0.640	0.607
$\alpha = 0.6$	0.963	0.561	0.733	0.699
$\alpha = 0.7$	1.070	0.606	0.827	0.792
$\alpha = 0.8$	1.174	0.655	0.928	0.896
$\alpha = 0.9$	1.307	0.707	1.041	1.017

Table 7: Ranking of the three methods.

Alternative	Typical arithmetic average method	Ranking typical arithmetic average method	Symbolic method	Ranking symbolic method	Proposed method					Ranking proposed method
					$\alpha = 0.5$	$\alpha = 0.6$	$\alpha = 0.7$	$\alpha = 0.8$	$\alpha = 0.9$	
Alternative 1	$S4.15$	1	$S4$	1	0.857	0.963	1.070	1.174	1.307	1
Alternative 2	$S2.40$	4	$S3$	3	0.517	0.561	0.606	0.655	0.707	3
Alternative 3	$S2.95$	3	$S3$	3	0.640	0.733	0.827	0.928	1.041	4
Alternative 4	$S3.20$	2	$S4$	1	0.607	0.699	0.792	0.896	1.017	2

Table 8: Differences in the main advantages of the three methods.

Consideration factor	Method		
	Typical arithmetic average method	Symbolic method	Proposed novel enhanced supplier selection method
Linguistic information	No	Yes	Yes
Order weight	No	No	Yes
Hesitant information	No	No	Yes

aggregate evaluation values of the network security system, based on the MVOWA weights ($\alpha = 0.5, 0.6, 0.7, 0.8, 0.9$), are calculated and shown in Table 6.

Step 7 (analyze the calculation results and select the best alternative). According to the calculation results of Step 6, the fuzzy majority rule is used as the proposed order: Alternative 1 $\succ$ Alternative 3 $\succ$ Alternative 4 $\succ$ Alternative 2.

4.4. Comparisons and Discussion. In order to further evaluate the effectiveness of the proposed novel enhanced supplier selection method, Section 4 illustrates a verification example of implementing a network security system in the military. This study also compares the experimental results with those of the typical arithmetic average and symbolic methods. The case data of the network security system are shown in Table 1, and the ranking of the 3 methods is shown in Table 7. The main differences between our method and the other solutions are described in Table 8. According to the comparison, the proposed integration of the HFLTS and MVOWA has several advantages.

4.4.1. Linguistic Information Considered. Supplier selection is an MADM problem and includes a significant amount of quantitative and qualitative data. Experts use LTSs to express the assessment attributes values to more reasonably reflect the actual situation. However, the attribute values of the possible alternative are required to be exact numerical values in the typical arithmetic average method, rendering it unable to handle linguistic information. The proposed method and symbolic method can incorporate linguistic information in the information aggregation process.

4.4.2. Ordered Weight Considered. The ordered weight is one of several important influencing factors that are used in multiple-attribute decision-making (MADM) and preference ranking [19, 20]. However, the traditional arithmetic average and symbolic methods did not consider the ordered weights of evaluation attribute values in the supplier selection issues, which will lead to deviations in the evaluation results. The proposed novel enhanced supplier selection method uses MVOWA weights to aggregate the evaluation values of the evaluation attributes. Thus, our approach is more suitable than the traditional arithmetic average and symbolic methods for supplier selection when considering ambiguous information.

4.4.3. Equivocal Information Considered. The typical arithmetic average method and symbolic method require that the attribute values of possible alternatives be precise and constitute a single LTS. However, an expert is sometimes uncertain about the exact value and single LTS of the assessment attribute data in supplier selection. For ambiguous information, the traditional arithmetic average and symbolic methods deleted assessment attribute data directly, decreased the samples number, and removed valuable information. The proposed novel enhanced supplier selection method uses the HFLTS to deal with ambiguous information. Thus, all of the information that the experts provide will be considered, and the results more accurately reflect the actual situation.

5. Conclusion

Supplier selection is a critical part of supply chain management and influences the successful operation of the supply chain. Selecting the most suitable supplier will ensure the competitive advantages and sustainable development of the entire supply chain. However, the typical supplier selection approaches did not consider the ordered weights between the evaluations of attribute values. The ordered weights are crucial factors in supplier selection problems, which will influence the assessment results of supplier selection. On the other hand, the experts are often hesitant between several assessment values when assessing attribute rating values, which increases the complexity and difficulty of supplier selection. To strengthen the evaluation of supplier selection, this study has integrated the HFLTS and MVOWA methods to select the most suitable supplier. Moreover, a network security system selection problem in the military was used as an illustrative example to compare the typical arithmetic average method, symbolic method, and our proposed approach. The simulation results showed that the proposed novel enhanced supplier selection method can provide more accurate and reasonable outcomes and can better reflect the actual situation than the typical arithmetic average method and symbolic method.

There are several advantages of integrating the MVOWA and HFLTS as follows. First, the proposed novel enhanced supplier selection method can effectively handle linguistic information in supplier selection. Moreover, our approach considers the ordered weight of assessment attribute values in the supplier selection issues. Finally, our method can more flexibly and precisely handle hesitant information. Thus, all information that the experts provide will be considered, and no useful information is lost. In the future, in further research, we expect to perform a more empirical study in a specific industry and extend the concept of our approach to address other decision-making issues. In addition, future research can explore using different algorithms to calculate the order weights in MADM problems.

Data Availability

The supplier selection data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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