# A Possibility Distribution Based Multi-Criteria Decision Algorithm for Resilient Supplier Selection Problems

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## Abstract

Resilient supplier selection problem is a key decision problem for an organization to gain competitive advantage. In the presence of multiple conflicting evaluation criteria, contradicting decision makers, and imprecise information sources, this problem becomes even more difficult to solve with the classical optimization approaches. Multi-Criteria Decision Analysis (MCDA) is a viable alternative approach for handling the imprecise information associated with the evaluation proffered by the decision makers. In this work, we present a comprehensive algorithm for ranking a set of suppliers based on aggregated information obtained from crisp numerical assessments and reliability adjusted linguistic appraisals from a group of decision makers. We adapted two popular tools - Single Valued Neutrosophic Sets (SVNS) and Interval-valued fuzzy sets (IVFS) and extended them to incorporate both crisp and linguistic evaluations from the decision makers to obtain aggregated SVNS and IVFS. This information is then used to rank the suppliers by using TOPSIS method. We present a case study to illustrate the mechanism of the proposed algorithm and show sensitivity of the supplier ranking with respect to the priorities of evaluation criteria.

**Key Words: Resilient Supplier Selection, Multi Criterial Decision Making, TOPSIS.**

## 1. Introduction

Due to the competitive nature of the current open market economy, a manufacturer's ability to avoid and/or absorb disruptions in supply chain has become a crucial requirement to survive and thrive in the market. The flow of material and information through the present-day supply chains can be disrupted by diverse unpredictable natural catastrophes such as earthquakes, floods, hurricanes, or unexpected man-made disasters such as labor strikes, bankruptcy or terrorist attack [1]. These disruptive events with low probability of occurrences can cause huge financial impact on supply chain operations. The Japanese earthquake occurred in 2011 struck the supply chains of motor vehicle companies such as GM and Toyota [2]. The unexpected disaster resulted in substantially reduced production capacity in the U.S., while full restoration of the supply chain capacity took months. As a small example, the earthquake disrupted the operations of Renesas Electronics, manufacturer of 40% of the world's supply of automotive microcontrollers; the disruption was felt by the worldwide automotive industry. To avoid or absorb the disruptions caused by disasters, either natural or anthropogenic, a manufacturer must design its supply chain network to be resilient. To a great extent, resilience capacity of a supply chain is preserved by resilient suppliers. Yossi [3] and Rice [4] have introduced the definition of supply chain resilience and resilient supplier characteristics. A resilient supplier has high capability to resist or absorb disaster impact and can get back to usual performance quickly following a disaster. To select an optimal resilient supplier among multiple alternatives, plentiful aspects need to be taken into consideration.

Supplier selection is a complicated, yet crucial decision problem because of its far-reaching influence on the quality, efficiency and reliability of the supply chain. The decision problem involves weighing several alternatives against multiple conflicting criteria. This becomes even more complicated when evaluation is done by multiple decision makers, each using their own perceptions about importance of criteria and the performance of the alternatives. Furthermore, pertinent information is often imprecise and available in linguistic form. *Multi Criteria Decision Analysis* (MCDA) is one of the most promising approaches to solve this complex decision-making process, as addressed by several researchers [5-11]. Howard and Ralph [12] first introduce MCDA as an extension of decision theory that considers multiple conflicting objectives. MCDA is methodology for evaluating alternatives based on individual preference, often against conflicting criteria, and combining them into one single appraisal. Due to its versatility, MCDA approaches are widely adopted in the fields of transportation, immigration, education, investment, environment, energy, defense and healthcare [5-10].

The applications of MCDA in supplier selection are numerous and extensive. As one of the most popular MCDA method, AHP (Analytical Hierarchy Process) is widely adopted among the research on supplier selection [13, 14]. AHP was firstly proposed by Saaty [15] and then refined by Golden et al [16], which is always used for ranking alternatives with qualitative data. In AHP, a complex master problem could be decomposed to plenty of subproblems in several levels, in which way the unidirectional hierarchical relationships between levels are more understandable. Then pairwise comparison between alternatives are conducted to determine the importance of the criteria and preference over all alternatives. With the help of AHP, the evaluation of alternatives could be extended to qualitative field while multiple criteria are considered, and the consistency of the system are satisfied. However, as the qualitative data are given by the decision makers based on experience, knowledge and judgment, the discrepancy among the decision makers, which would result in subjective influence in data, are not considered. Thus, the uncertainty and imprecise nature in the data are not dealt with, which may lead to low reliability and robustness of the result. To develop a more accurate and reliable approach to evaluated the alternatives, TOPSIS (Technique for order preference by similarity to an ideal solution) was developed by Yoon [17] and Hwang et al. [18] based on the concept that the optimal solution should have the closest distance from the Positive Ideal Solution (PIS) and longest distance from the Negative Ideal Solution (NIS). The PIS and NIS are determined by the objective of the components of the variables, and the distances are usually measured by Euclidean Distance while handling supplier selection problems. Different from AHP, the input data are quantitative numbers so that the computation could be processed. Due to its high accuracy, the application of TOPSIS in supplier selection is also numerous. One of these studies [19] proposed an application of TOPSIS in the supplier selection process in Iran Auto Supply Chain. In his research, both Numerical and Linguistic evaluation criteria are considered. To evaluate all the criteria simultaneously with quantitative data, the authors assigned numerical numbers (without consideration of fuzziness of data set) to each class in the linguistic criteria directly and generated the quantitative decision matrix. After the normalization and calculation of entropy measurement for the quantitative decision matrix, the weight of each criterion is determined, and TOPSIS is then adopted to measure the performance of each alternative supplier. Finally, the list of preference of the alternative suppliers are generated based on their ranking score and the optimal supplier is selected. In addition, to better evaluate the alternative suppliers, some of the researchers aggregate AHP with TOPSIS to develop a comprehensive decision-making framework [20, 21]. However, most of these methods are developed with respect to crisp data, and the uncertainty, impreciseness and fuzziness nature of the data extracted from real world are not considered.

While crisp data is inadequate to model real life situations, intuitionistic fuzzy set was introduced by Atanassov [22] and is adopted to the aggregated decision-making framework by Haldar et al. and Boran et al. [23, 24]. As it is often difficult for an expert to exactly quantify his or her opinion as a number in interval [0,1], it's more suitable to represent this degree of certainty by an interval. Wang and Li [25] defined the concept of *Interval-valued Fuzzy Sets* (IVFS) and it has been widely applied in real-world problems. IVFS includes two indexes, which are the lower limit of degree of membership and the upper limit of degree of membership respectively. Because the interval-valued fuzzy set theory can provide a more accurate modeling, Ashtiani et al. [26] extend the application of IVFS in TOPSIS to solve Multi Criteria Decision Making problems. The algorithm of the interval-valued fuzzy TOPSIS is proposed and a numerical example considering linguistic criteria are presented in his research to demonstrate the practicability and of the model.

To characterize the indeterminacy more explicitly and apply more easily in the real world, Wang et al. [27, 28] proposed the concept of *single valued neutrosophic set* (SVNS) and defined various properties of SVNS. SVNS consists of three components, which are truth-membership degree, the indeterminacy-membership degree and the falsity membership degree respectively, which gives us an additional possibility to represent uncertainty, imprecise, incomplete, and inconsistent information existing in real world. As SVNS is more suitable to handle the uncertainty, imprecise, inconsistent and incomplete information existing in real world, Sahin and Yiğider [21] introduced SVNS in TOPSIS to replace the crisp data in the decision matrix and the results show that the single valued neutrosophic TOPSIS can be preferable for dealing with incomplete, undetermined and inconsistent information in MCDA problems. However, only linguistic criteria are evaluated were considered, while many of the essential and significant criteria evaluation may be expressed in numerical form in the process of supplier evaluation.

The existing research have shown promising potential of MCDA methods in supplier selection problems. However, there are still scope of extending the current methods to make the decision process more fitting to the real-world problems. The study done by Shahroudi and Tonekaboni [19] presented the application of TOPSIS in supplier selection, where both linguistic and numerical criteria were considered. The works of Ashtiani et al. [26] and Sahin and Yiğider [21] showed the effectiveness of IVFS and SVNS within the TOPSIS process. However, there is still a lack of a systematic approach where alternative suppliers can be evaluated concerning both linguistic and numerical criteria with uncertainty in the data. To the best of our knowledge, there is no method currently present that could evaluate the alternative suppliers from resilient perspective based on numerical criteria and linguistic criteria simultaneously while considering the impreciseness and unreliable nature of the data. To address this problem, we proposed an algorithm based on possibilistic approach that extends the fuzzy-based TOPSIS to numerical criteria along with the linguistic criteria. Furthermore, in our proposed method, the reliability-based membership degree is adopted to bridge the gap in considering crisp data and the fuzzy set (SVNS and IVFS) on numerical criteria simultaneously to help decision maker evaluating the alternative set of suppliers from resilient point of view in a comprehensive way.

We organize the rest of the paper as follows: in the Section 2, we introduce the methodology and present the preliminary concepts for designing the algorithm. Then in Section 3, we present the detailed computation process of the algorithm. In Section 4, we present an illustrative example of a resilient supplier selection problem following our algorithm. Finally, in Section 5 we conclude our paper with discussion on our findings and potential future research.

## 2. Methodology

In our MCDA model, we adapted two fuzzy-based approaches, IVFS and SVNS, to characterize the assessment given by decision makers as well as the weight of criteria and decision makers. Although these two approaches share some similarities; the primary difference is how the linguistic evaluations are represented by fuzzy numbers. Firstly, we computed the weight of criteria based on IVFS and SVNS theory and fuzzified the universe of discourse of numerical criteria according to the obtained weight. With the fuzzified frame of discernment, the membership function and associated membership degree for each linguistic class is calculated. After that, the derived membership degrees are modified with respect to reliability indices and normalized to be regarded as the weight of each class in a certain criterion for the supplier's performance measurement. Multiplied by the components of corresponding IVFS or SVNS of each linguistic class, the weighted average of each component is generated and the integrated IVFS or SVNS decision matrixes for numerical criteria are constructed. Then the obtained decision matrixes are coordinated with respect to the weight of criteria based on the algorithm for these two fuzzy approaches. Possessing the weighted decision matrixes, TOPSIS method is processed to compute the closeness coefficient (CC), which is deemed to be the ranking score of the suppliers to determine the list of preference of suppliers. To make it more understandable, we would introduce some significant preliminaries in our methodology.

### 2.1. Multi Criteria Decision Analysis

Multi Criteria Decision Analysis (MCDA) provides a comprehensive decision analysis framework that could help the stakeholders balance the pros and cons of the alternatives in a multi-dimensional optimization problem, in which alternatives, evaluation criteria and decision makers are the essential variables. The analysis process of MCDA and the corresponding steps in our decision-making model could be summarized as follows [29]:

Table 1. Framework of MCDA.

| | | |
|---|---|---|
| Step 1 | Defining the decision problem | Select optimal supplier with highest resilience over a group of alternative suppliers |
| Step 2 | Selecting and structuring criteria | Identify the evaluation criteria with respect to supplier resilience |
| Step 3 | Measuring performance | Gather data about the alternatives' performance on the criteria and summarize this in a decision matrix |
| Step 4 | Scoring alternatives | Evaluate the performance of the alternative suppliers based on the objective of the criteria |

| | | |
|---|---|---|
| Step 5 | Weighting criteria and decision makers | Determine the weight of criteria and decision makers based on their importance |
| Step 6 | Calculating aggregate scores | Use the alternatives' scores on the criteria and the weights for the criteria and decision makers to get "total value" by which the alternatives are ranked with TOPSIS |
| Step 7 | Dealing with uncertainty | Perform Sensitivity analysis to understand the level of robustness of the MCDA results |
| Step 8 | Reporting and examination of findings | Interpret the MCDA outputs, including sensitivity analysis, to support decision making |

### 2.2. Technique for order preference by similarity to an ideal solution (TOPSIS)

TOPSIS is a decision-making technique that the alternatives are evaluated based on their distance to the ideal solution. The closer the distance of an alternative to the ideal solution, the higher a grade it would gain. In our research, Euclidian Distance is used to measure the performance of the alternatives and the function is described as below [21]:

$$s_i^+ = \sqrt{\sum_{j=1}^{n} \left\{ \left(a_{ij} - a_j^+\right)^2 + \left(b_{ij} - b_j^+\right)^2 + \left(c_{ij} - c_j^+\right)^2 \right\}} \quad i = 1,\ 2,\ \dots,\ n \tag{2.1}$$

$$s_i^- = \sqrt{\sum_{j=1}^{n} \left\{ \left(a_{ij} - a_j^-\right)^2 + \left(b_{ij} - b_j^-\right)^2 + \left(c_{ij} - c_j^-\right)^2 \right\}} \quad i = 1,\ 2,\ \dots,\ n \tag{2.2}$$

$$\tilde{\rho}_j = \frac{s^-}{s^+ + s^-}, \quad 0 \leq \tilde{\rho}_j \leq 1 \tag{2.3}$$

Where $s_i^+$ and $s_i^-$ are the positive and negative ideal solution respectively, $\tilde{\rho}_j$ is the closeness coefficient(CC), $a_{ij}, b_{ij}, c_{ij}$ are the component of the alternatives on criteria $j$ and $a_j^+, b_j^+, c_j^+$ are the corresponding components of the Positive Ideal Solution (PIS) and $a_j^-, b_j^-, c_j^-$ are the corresponding components of Negative Ideal Solution (NIS).

### 2.3. Interval Valued Fuzzy Set (IVFS)

An interval valued fuzzy set A defined on $(-1, +1)$ is given by [30]:

$$\begin{gathered} \mathrm{A} = \{(\mathrm{x}, [\mu_A^L(x), \mu_A^U(x)]\} \\ \mu_A^L(x), \mu_A^U(x): X \rightarrow [0,1] \quad \forall x \in X, \mu_A^L(x) \leq \mu_A^U(x) \\ \mu_A(x) = [\mu_A^L(x), \mu_A^U(x)] \\ \mathrm{A} = \{(\mathrm{x}, \mu_A(x))\}, x \in (-\infty, +\infty) \end{gathered} \tag{2.4}$$

; where $\mu_A^L(x)$ is the lower limit of degree of membership and $\mu_A^U(x)$is the upper limit of degree of membership.

If the membership degree is expressed in triangular interval valued fuzzy numbers, it can be also demonstrated as:

$$x = [(x_1, x_1'); \; x_2; \; (x_3', x_3)] \tag{2.5}$$

; where $x_1$, $x_1'$, $x_2$, $x_3'$ and $x_3$ could be illustrated in the following figure:

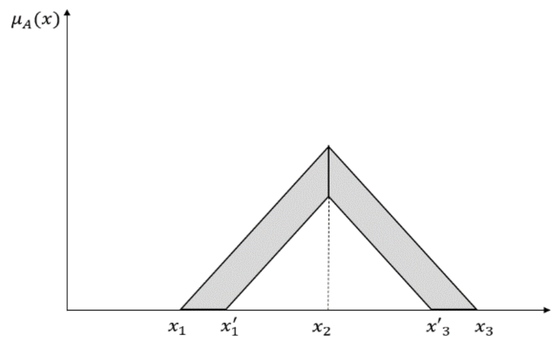


Figure 1. Illustration for the Triangular Interval Valued Fuzzy Number.

Table 2 shows the corresponding IVFS according to the linguistic terms:

Table 2. Linguistic Terms and Associated IVFS.

| Linguistic Terms | IVFS $(a, a', b, c', c)$ | | | | |
|---|---|---|---|---|---|
| Weight Linguistic Terms in IVFS | | | | | |
| VUI | 0 | 0 | 0 | 0.15 | 0.15 |
| UI | 0 | 0.15 | 0.3 | 0.45 | 0.55 |
| M | 0.25 | 0.35 | 0.5 | 0.65 | 0.75 |
| I | 0.45 | 0.55 | 0.7 | 0.8 | 0.95 |
| VI | 0.55 | 0.75 | 0.9 | 0.95 | 1 |
| Performance Linguistic Terms in IVFS | | | | | |
| VB | 0 | 0 | 0 | 1 | 1.5 |
| B | 0 | 0.5 | 1 | 2.5 | 3.5 |
| MB | 0 | 1.5 | 3 | 4.5 | 5.5 |
| M | 1 | 2.5 | 4 | 5.5 | 6.5 |
| MG | 2.5 | 3.5 | 5 | 6.5 | 7.5 |
| G | 4.5 | 5.5 | 6 | 7 | 8.5 |
| VG | 5.5 | 6.5 | 7 | 8 | 9.5 |
| VVG | 7.5 | 8.5 | 9 | 9.5 | 10 |
| EG | 8.5 | 9.5 | 10 | 10 | 10 |

In Table 2, $\{VUI, UI, M, I, VI\}$ is a set of linguistic weights for decision makers refers to Very Unimportant, Unimportant, Medium, Important and Very Important respectively, and $\{VB, B, MB, M, MG, G, VG, VVG, EG\}$ is a set of linguistic weights for criteria refers to Very Bad, Bad, Medium Bad, Medium, Medium Good, Good, Very Good, Very Very Good and Extremely Good respectively.

For two IVFS $v = [(v_1, v_1'); \ v_2; \ (v_3', v_3)]$ and $u = [(u_1, u_1'); \ u_2; \ (u_3', \ u_3)]$, the algorithm for finding the compound IVFS is as follows:

$$v * u = [(v_1 * u_1, v_1' * u_1'); \ v_2 * u_2; ( \ v_3' * u_3', v_3 * \ u_3)] \tag{2.6}$$

; where $* \in \{+, -, \times, \div\}$

Assume there are t decision makers, $V_k = [(v_{1k}, v_{1k}'); \ v_{2k}; \ (v_{3k}', v_{3k})]$ refers to the weight of kth decision maker in the form of IVFS, $I_{jk} = [(u_{1jk}, u_{1jk}'); \ u_{2jk}; \ (u_{3jk}', u_{3jk})]$ represent the weight of jth criteria given by kth decision maker in the form of IVFS, then the aggregated weight of jth criteria in the form of IVFS could be calculated based on (2.6) as follows:

$$I_j = [(\tfrac{1}{t}\sum_k v_{1k}u_{1jk}, \tfrac{1}{t}\sum_k v_{1k}'u_{1jk}'); \ \tfrac{1}{t}\sum_k v_{2k}u_{2jk}; (\tfrac{1}{t}\sum_k v_{3k}'u_{3jk}', \tfrac{1}{t}\sum_k v_{3k}u_{3jk})] \tag{2.7}$$

Similarly, if the performance measurement for ith alternative given by kth decision maker $P_{ik} = [(e_{1ik}, e_{1ik}'); \ e_{2ik}; \ (e_{3ik}', e_{3ik})]$, then the aggregated performance measurement of ith alternative in the form of IVFS could be calculated as follows:

$$P_i = [(\tfrac{1}{t}\sum_k v_{1k}e_{1ik}', \tfrac{1}{t}\sum_k v_{1k}'e_{1ik}'); \ \tfrac{1}{t}\sum_k v_{2k}e_{2ik}; (\tfrac{1}{t}\sum_k v_{3k}'e_{3ik}', \tfrac{1}{t}\sum_k v_{3k}e_{3ik})] \tag{2.8}$$

### 2.4. Single Valued Neutrosophic Set (SVNS)

A single valued neutrosophic set (SVNS) can be defined as follows [21]:

Let X be a universe of discourse. A single valued neutrosophic set A over X is an object having the form

$$A = \{\langle x, \mathrm{u}_A(x), \mathrm{r}_A(x), \mathrm{v}_A(x)\rangle : x \in X\} \tag{2.9}$$

where $\mathrm{u}_A(\mathrm{x}) : \mathrm{X} \rightarrow [0,1]$, $\mathrm{r}_A(x) : \mathrm{X} \rightarrow [0,1]$ and $\mathrm{v}_A(x) : \mathrm{X} \rightarrow [0,1]$ with $0 \leq \mathrm{u_A(x)} + \mathrm{r_A(x)} + \mathrm{v_A(x)} \leq 3$ for all $\mathrm{x} \in \mathrm{X}$. The intervals $\mathrm{u}_A(x)$, $\mathrm{r}_A(x)$ and $\mathrm{v}_A(x)$ denote the truth- membership degree, the indeterminacy-membership degree and the falsity membership degree of x to A, and can be simplified as $\mathrm{a, b, c}$ respectively. Table 3 shows the corresponding SVNS according to the linguistic terms:

Table 3. Linguistic Terms and Associated SVNS.

| Linguistic Terms | SVNS (a, b, c) | | |
|---|---|---|---|
| Weight Linguistic Terms in SVNS | | | |
| VI | 0.9 | 0.1 | 0.1 |
| I | 0.75 | 0.25 | 0.2 |
| M | 0.5 | 0.5 | 0.5 |
| UI | 0.35 | 0.75 | 0.8 |
| VUI | 0.1 | 0.9 | 0.9 |
| Performance Linguistic Terms in SVNS | | | |
| VB | 0.2 | 0.85 | 0.8 |
| B | 0.3 | 0.75 | 0.7 |
| MB | 0.4 | 0.65 | 0.6 |
| M | 0.5 | 0.5 | 0.5 |

| | | | |
|---|---|---|---|
| MG | 0.6 | 0.35 | 0.4 |
| G | 0.7 | 0.25 | 0.3 |
| VG | 0.8 | 0.15 | 0.2 |
| VVG | 0.9 | 0.1 | 0.1 |
| EG | 1 | 0 | 0 |

Assume the decision makers' group consists of $t$ participants, $\mathrm{A}_k = (\mathrm{a}_k, \mathrm{b}_k, \mathrm{c}_k)$ express the SVNS importance of the $k$th decision maker. Then the weight of $k$th decision maker can be calculated as follows:

$$\sigma_k = \frac{a_k + b_k(\frac{a_k}{a_k + c_k})}{\sum_{k=1}^{t} a_k + b_k(\frac{a_k}{a_k + c_k})},\ \sigma_k \geq 0\ and\ \sum_{k=1}^{t} \sigma_k = 1. \tag{2.10}$$

The aggregated SVNS decision matrix $D$ with respect to decision makers is defined by $\mathrm{D} = \sum_{k=1}^{t} \delta_k D^k$, where

$$\mathrm{D} = \begin{pmatrix} d_{11} & \cdots & d_{1j} \\ \vdots & \ddots & \vdots \\ d_{i1} & \cdots & d_{ij} \end{pmatrix} \tag{2.11}$$

And

$$d_{ij} = (u_{ij}, r_{ij}, v_{ij}) = (1 - \prod_{k=1}^{t}(1 - a_{ij}^{(k)})^{\sigma_k},\ \prod_{k=1}^{t}(b_{ij}^{(k)})^{\sigma_k}, \prod_{k=1}^{t}(c_{ij}^{(k)})^{\sigma_k}) \tag{2.12}$$

Let $\mathrm{w}_j^{(\mathrm{k})} = (\mathrm{a}_j^{(k)}, \mathrm{b}_j^{(k)}, \mathrm{c}_j^{(k)})$ be an SVN number expressing the importance of criteria $\mathrm{j}$ $(\mathrm{j} = 1, 2, \ldots)$ by the kth decision maker. The SVNS describing the weight of the jth criteria can be calculated using the method proposed by:

$$w_j = (1 - \prod_{k=1}^{t}(1 - a_{jk})^{\sigma_k},\ \prod_{k=1}^{t} b_{jk}{}^{\sigma_k},\ \prod_{k=1}^{t} c_{jk}{}^{\sigma_k}) \tag{2.13}$$

While the weight vector of all criteria is presented as:

$$\mathrm{W} = (w_1, w_2, \ldots, w_j) \tag{2.14}$$

Then the aggregated weighted SVNS decision matrix can be obtained as:

$$D^* = \mathrm{D} \otimes \mathrm{W} \tag{2.15}$$

Based on the product algorithm of SVNS:

$$A_1 \otimes A_2 = (a_1 a_2,\ b_1 + b_2 - b_1 b_2, c_1 + c_2 - c_1 c_2) \tag{2.16}$$

The algorithm of SVNS is totally different to that of IVFS based on (2.6-2.8), so we adopt these two fuzzy approaches to demonstrate the effectiveness and robustness of our decision-making model.

### 2.5. Membership Function

The definition of membership function was first introduced by Zadeh [31], where the membership functions were used to operate on the domain of all possible values. In fuzzy logic, membership degree represents the truth value of a certain proposition. Different from the concept of probability, truth value represents membership in vaguely defined sets. For any set X, the membership degree of an element x of X in fuzzy set A is denoted as $\mu_A(x)$, which quantifies the grade of membership of the element x to the fuzzy set A.

Ullah et al. [32] presented a method to fuzzify the universe of discourse of the numerical criteria and formulate the membership function to calculate the membership degree with range data as shown in Figure 2:

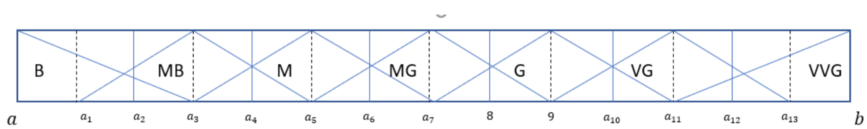


Figure 2. Frame of Discernment.

For the frame of discernment shown in the above figure, the membership functions of the different classes are calculated as follows:

$$m_B = max\left(0,\ \frac{a_3 - x}{a_3 - a}\right)$$
$$m_{MB} = \max\left(0,\ \min(\frac{x-a_1}{a_3-a_1}, \frac{a_5-x}{a_5-a_3}\right) \quad (2.17)$$
$$m_{VVG} = \max\left(0,\ \frac{x - a_{11}}{b - a_{11}}\right)$$

; where $a_i = a + \frac{b-a}{2\times7},\ \ i = 1,2, \dots, (2 \times 7 - 1)$, and 7 is the number of class in this frame of discernment. The membership functions are assumed to be triangular and symmetric. The membership function for each class depends on the frame of discernment of the criteria.

### 2.6. Reliability-based Membership Function

As the membership functions are assumed triangular and symmetric, the uncertainty and impreciseness of the functions need to be taken into consideration. Jiang et al [33] proposed a reliability-based membership function to deal with uncertainty of information and the reliability of information sources. The reliability of the membership functions is measured by the static reliability index and dynamic reliability index, which are defined by the similarity among classes and the risk distance between the test samples and the overlapping area among classes respectively. The comprehensive reliability is computed by the product of the two index and the reliability-based membership function are fused using Dempster's combination rule [34, 35]. The numerical examples provided by Jiang et al. verified the effectiveness of the reliability-modified functions.

The static reliability index is measured by the overlap area between two adjacent classes as follows:

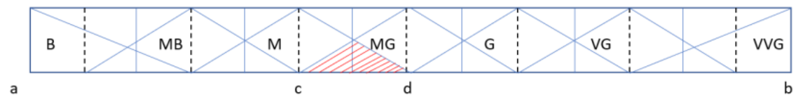


Figure 3. Illustration of Static Reliability Index.

The shaded part is the overlap between class M and MG. The larger this area, the more possible that an input data is wrongly recognized as M or MG while it's actually MG or M. So, the Similarity between M and MG $sim_{M,MG}$ in a certain criterion can be described as [33]:

$$sim_{M,MG} = \frac{\int_c^d \min\limits_{c \le x \le d}(m_M(x), m_{MG}(x))dx}{\int m_M(x) + m_{MG}(x) - \int_c^d \min\limits_{c \le x \le d}(m_M(x), m_{MG}(x))dx} \tag{2.18}$$

The static reliability index $R^s$ then can be calculated as:

$$R^s = \sum_{i<l}(1 - sim_{il}) \tag{2.19}$$

While $i$ and $l$ are the adjacent classes in the same universe of discourse in one criterion.

The dynamic reliability index is measured with a set of test sample and the risk distance between every peak of overlap and the test value.

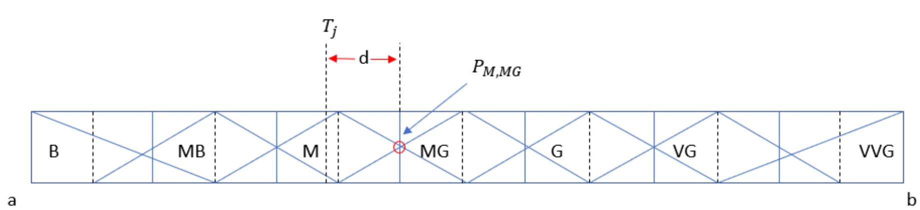


Figure 4. Illustration of Dynamic Reliability Index.

If $P_{M,MG}$ is the peak of the overlap of M and MG, and $T_j$ is the test sample for this criterion $C_j$, the distance $d$ between $T_j$ and $P_{M,MG}$ represents the risk distance that related to the uncertainty of the test sample.

The risk distance can be formulated as [33]:

$$d_{M,MG} = \frac{|\mathrm{T}_j - P_{M,MG}|}{D} \tag{2.20}$$

; where D is the range of the universe of discourse of $\mathrm{C}_j$, which is $(\mathrm{a} - \mathrm{b})$.

After calculating all the risk distance, the total dynamic reliability index can be determined as:

$$R^d = e^{\sum_2^n d_{(l-1)l}} \tag{2.21}$$

Then the Comprehensive reliability index can be defined as:

$$R = R^s \times R^d \tag{2.22}$$

After the normalization:

$$R^* = \frac{R}{\max(R)} \tag{2.23}$$

The reliability-based membership degree can be calculated as:

$$m_l^R = R^* \times m_l \tag{2.24}$$

; where *l* is a class in a universe of discourse.

### 2.7. Evaluation Criteria

The evaluation criteria are divided into two groups: Resiliency Criteria and Critical Criteria [30]. The description of the criteria is summarized as follows:

Table 4. Description of Evaluation Criteria.

| Criteria | | Description |
|---|---|---|
| Resiliency Criteria | Supply chain density | The quantity and geographical spacing of nodes within a supply chain |
| | Supply chain complexity | The number of nodes in a supply chain and the interconnections between those nodes |
| | Responsiveness | The response speed of the supplier to market demand |
| Critical Criteria | Number of critical nodes in a Supply chain | Node criticality is the relative importance of a given node or set of nodes within a supply chain |
| | Re-engineering | The corrective procedure for the incorporation of any engineering design change within the product |
| | Buffer capacity | The level of extra stock that is maintained to mitigate the risk of stock-outs due to uncertainties in supply and demand. |
| | Supplier's resource flexibility | The different logistics strategies which can be adopted either to release a product to a market or to procure a component from a supplier |
| | Lead time | The delay between the initiation and execution of a process |

## 3. Computation Process

To better illustrate the detailed steps of our proposed decision-making algorithm, we provide a comprehensive flow that describes the computation process. The computation process includes both the IVFS and SVNS approaches and is summarized as follows:

*Step 1: Categorize the criteria into different group.*

Firstly, we determined the feature and objective of each criterion to prepare for further computation.

Table 5. Categorization of Criteria.

| Categorization | | Criteria | Obj. |
|---|---|---|---|
| Numerical | $C_1$ | Number of critical nodes in a Supply chain | Min |
| | $C_2$ | Buffer capacity | Max |
| | $C_3$ | Lead time | Min |
| Linguistic | $C_4$ | Supply chain density | Min |
| | $C_5$ | Supply chain complexity | Max |
| | $C_6$ | Responsiveness | Max |
| | $C_7$ | Re-engineering | Max |
| | $C_8$ | Supplier's resource flexibility | Max |

*Step 2: Calculate the weight of each decision maker and criterion.*

To determine the frame of discernment of the numerical criteria, we need to obtain their weight in advance. Suppose we have i alternative suppliers $S_i$, j evaluation criteria $C_j$ and k decision makers $DM_k$. Assume $D_k$ refers to the linguistic weight of $DM_k$, $L_{jk}$ refers to the importance of criteria j given by $DM_k$, based on Table 3 and equation (2.10) and (2.13), the weight of each DM and criterion in SVNS approach could be calculated as $w_{cj}$.

Table 6. Calculated SVNS for Weight of Criteria.

| Criteria | Weight | | |
|---|---|---|---|
| | a | b | c |
| $C_1$ | $w_{a1}$ | $w_{b1}$ | $w_{c1}$ |
| $C_2$ | $w_{a2}$ | $w_{b2}$ | $w_{c2}$ |
| … | … | … | … |
| $C_j$ | $w_{aj}$ | $w_{bj}$ | $w_{cj}$ |

For IVFS approach, based on (2.7), we just need to transfer the linguistic data to IVFS data for further computation.

*Step 3: For the numerical criteria, fuzzify their universe of discourse based on their importance and determine the membership function of the classes.*

After we get the weight of the numerical criteria, the number of classes and frame of discernment could be determined. Based on the obtained weight, the number of classes in each corresponding criterion can be assigned. The higher the weight of criteria, the more number of classes are divided.

In the fuzzification process, the span of the universe of discourse is generated by the minimum and maximum of all the crisp data for a certain criterion including all the alternative suppliers. For example, if the minimum and maximum of crisp data in $C_j$ are $a_0$ and $a_{18}$ concerning all the suppliers in $C_j$ then the span of universe of discourse of $C_j$ is $(a_0, a_{18})$. Assume we decide to assign 9 classes to $C_j$ based on the weight of $C_j$, then the universe of discourse underlying the regular scheme of $C_j$ can be fuzzified as follows [32]:

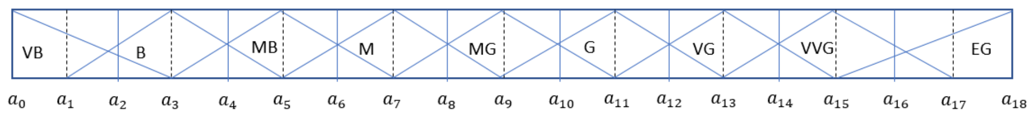


Figure 5. Illustration of Fuzzification.

$$a_i = a_0 + \frac{a_{18}-a_0}{18},\ i = 1, 2, \ldots, 18 \tag{3.1}$$

The membership function of each class $m_F$ in Figure 4 can be formulated as [32]:

$$m_{VB} = max\left(0,\ \frac{a_3-x}{a_3-a_0}\right)$$

$$m_B = \max\left(0,\ \min(\frac{x-a_1}{a_3-a_1}, \frac{a_5-x}{a_5-a_3}\right) \tag{3.2}$$

$$m_{EG} = \max\left(0,\ \frac{x-a_{15}}{a_{18}-a_{15}}\right)$$

*Step 4: Transfer the crisp data in the numerical criteria to range data and calculate membership degree.*

Firstly, put the crisp data in an ascending order. Take numerical criteria $C_j$ for example, if we have the crisp data of the suppliers concerning criteria $C_j$:

Table 7. Crisp Data of $C_j$.

| $C_j$ | | | | | Min | Max |
|---|---|---|---|---|---|---|
| Supplier | $DM_1$ | $DM_2$ | … | $DM_k$ | | |
| $S_1$ | $N_{1j1}$ | $N_{1j2}$ | … | $N_{1jk}$ | $N_{1jn}$ | $N_{1jm}$ |
| $S_2$ | $N_{2j1}$ | $N_{2j2}$ | … | $N_{2jk}$ | … | … |
| … | … | … | … | … | … | … |
| $S_i$ | $N_{ij1}$ | $N_{ij2}$ | … | $N_{ijk}$ | … | … |

; where $S_i$ refers to ith supplier, $N_{ijk}$ refers to the crisp data of supplier i on criteria j given by decision maker k, $N_{1jn}$ and $N_{1jm}$are the minimum and maximum values for $S_1$ on $C_j$.

Assume that $N_{1j1}$<$N_{1j2}$<…<$N_{1jk}$ for $S_1$ (if there is any outlier in the crisp data, we will exclude the outliers with Excel TRIMMEAN), the range value of $S_1$ on $C_j$ could be described as $r_{ij}$ ($N_{111}$, $N_{11k}$). For $S_1$, there are k crisp data given by decision makers through $DM_1$ to $DM_k$. These k data consist the data sample for $S_1$ concerning $C_j$. Regarding these k crisp data as a data set for $S_1$, the range of this data set is from the minimum to the maximum, which are $N_{111}$ and $N_{11k}$. So, the range value for $S_1$ is ($N_{1j1}$, $N_{1jk}$). This way, all the k crisp data given by the decision makers are aggregated in the range value and all their contribution are included in this range value. In this process, we don't consider the weight of decision makers. After that, the decision makers are no longer involved in the computation process of Numerical Criteria because their contribution has been presented in the range value, which would be the fundamental input through the whole model.

After we get the range value, we can calculate membership degree for each class according to the membership function [32]:

$$m_{ij} = \frac{\int_{x \in R} m_F(x)dx}{\|\acute{R}\|} \tag{3.3}$$

; where R refers to the span of the criteria and $\|\acute{R}\|$ refers to the largest segment of R that belongs to the support $m_F$.

This way, the membership degree of $S_i$ on $C_j$ at linguistic class $l$ could be calculated as $M_{ijl}, l = 1, 2, 3, \ldots, 9$.

*Step 5: Calculate the normalized reliability-based membership degree.*

According to function (2.18-2.24), comprehensive reliability indexes for $C_j$ could be generated as $Rc_j$. Then based on (2.25), the original membership degree can be modified. To get the normalized weight of each class and make them add up to 1, we should normalize the membership value as:

$$n_{ijl} = \frac{m_{ijl}}{\sum_{l=1}^{9} m_{ijl}} \tag{3.4}$$

Then the original membership degree $M_{ijl}$ can be normalized as $A_{ijl}$, Where $\sum_{l=1}^{9} A_{ijl} = 1$, $l = 1, 2, 3, \ldots, 9$

*Step 6: Generate the integrated SVNS and IVFS for every alternative supplier concerning each criterion.*

To get SVNS for the numerical criteria, we integrated SVNS and the membership degree we calculated above to generate the integrated SVNS for the numerical criteria. In this integration process, the membership degree is regarded as the weight of each linguistic class for every alternative on the criteria.

Then the membership degree is multiplied by the components of the corresponding SVNS presented in Table 3 to obtain the integrated SVNS. The components of the integrated SVNS for each $S_i$ on $C_j$ could be calculated as:

$$a_{ij} = \sum_l A_{ijl}\, a_l, l = 1, 2, \ldots, 9 \tag{3.5}$$

$$b_{ij} = \sum_l A_{ijl}\, b_l, l = 1, 2, \ldots, 9 \tag{3.6}$$

$$c_{ij} = \sum_l A_{ijl}\, c_l, l = 1, 2, \ldots, 9 \tag{3.7}$$

; where $a_l$, $b_l$ and $c_l$ are the corresponding components of class *l* in Table 3.

The integrated SVNS for $S_i$ on $C_j$can be described as $(a_{ij}, b_{ij}, c_{ij})$, Where $j = 1, 2, 3$. Similarly, based on Table 2, the components of the integrated IVFS for each $S_i$ on $C_j$ could also be calculated based on following functions:

$$a_{ij} = \sum_l A_{ijl}\, a_l, l = 1, 2, \ldots, 9 \tag{3.8}$$

$$a'_{ij} = \sum_l A_{ijl}\, a'_l, l = 1, 2, \ldots, 9 \tag{3.9}$$

$$b_{ij} = \sum_l A_{ijl}\, b_l, l = 1, 2, \ldots, 9 \tag{3.10}$$

$$c'_{ij} = \sum_l A_{ijl}\, c'_l, l = 1, 2, \ldots, 9 \tag{3.11}$$

$$c_{ij} = \sum_l A_{ijl}\, c_l, l = 1, 2, \ldots, 9 \tag{3.12}$$

; where $a_l$, $a'_l$, $b_l$, $c'_l$ and $c_l$ are the corresponding components of class *l* in Table 2.

*Step 7: Construction of aggregated decision matrix with respect to decision makers for linguistic criteria.*

If $L_{ijk}$ refers to the linguistic data of $S_i$ on $C_j$ given by $DM_k$, based on (2.11) and (2.12) and Table 3, the aggregated SVNS with respect to decision makers can be obtained as $(a_{ij}, b_{ij}, c_{ij})$, where $j = 4, 5, \ldots, 8$.

Similarly, based on (2.8) and Table 2, the aggregated IVFS with respect to decision makers can be obtained as well.

*Step 8: Aggregate the numerical criteria matrix and the linguistic criteria matrix.*

As we have got all the SVNS for both numerical and linguistic criteria, we are able to build up a complete SVNS matrix. Similarly, the decision matrix as IVFS could also be generated.

*Step 9: Construction of aggregated weighted decision matrix with respect to criteria*

By using the weight of criteria matrix Table 6 and the aggregated weighted SVNS matrix Table 8, the aggregated weighted SVNS decision matrix can be obtained based on (2.15) and (2.16):

Table 8. SVNS Decision Matrix.

| Complete SVNS Decision Matrix | | | |
|---|---|---|---|
| Supplier | SVNS | | |
| | $C_1$ | … | $C_j$ |
| $S_1$ | $(a_{11}, b_{11}, c_{11})$ | … | $(a_{1j}, b_{1j}, c_{1j})$ |
| $S_2$ | $(a_{21}, b_{21}, c_{21})$ | … | $(a_{2j}, b_{2j}, c_{2j})$ |
| … | … | … | … |
| $S_i$ | $(a_{i1}, b_{i1}, c_{i1})$ | … | $(a_{ij}, b_{ij}, c_{ij})$ |

| Aggregated Weighted SVNS Decision Matrix | | | |
|---|---|---|---|
| $S_1$ | $(a_{11}, b_{11}, c_{11})^*$ | … | $(a_{1j}, b_{1j}, c_{1j})^*$ |
| $S_2$ | $(a_{21}, b_{21}, c_{21})^*$ | … | $(a_{2j}, b_{2j}, c_{2j})^*$ |
| … | … | … | … |
| $S_i$ | $(a_{i1}, b_{i1}, c_{i1})^*$ | … | $(a_{ij}, b_{ij}, c_{ij})^*$ |

; where $j = 1, 2, \dots, 8$

For the IVFS approach, we must normalize the decision matrix in advance. Given $x_{ij} = [(a_{ij}, a'_{ij});\ b_{ij};\ (c'_{ij}, c_{ij})]$, based on the following functions [26]

$$r_{ij} = \left[\left(\frac{a_{ij}}{c_j^+}, \frac{a'_{ij}}{c_j^+}\right); \frac{b_{ij}}{c_j^+}; \left(\frac{c'_{ij}}{c_j^+}, \frac{c_{ij}}{c_j^+}\right)\right], \quad \forall j \in G_1 \tag{3.13}$$

$$r_{ij} = \left[\left(\frac{a_j^-}{a'_{ij}}, \frac{a_j^-}{a_{ij}}\right); \frac{a_j^-}{b_{ij}}; \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{c'_{ij}}\right)\right], \quad \forall j \in G_2 \tag{3.14}$$

$$c_j^+ = \max_i c_{ij}, \quad \forall j \in G_1 \tag{3.15}$$

$$a_j^- = \min_i a'_{ij}, \quad \forall j \in G_2 \tag{3.16}$$

; where $G_1 = \{C_2, C_5, C_6, C_7, C_8\}$ , $G_2 = \{C_1, C_3, C_4\}$ based on Table 5.

Then, the aggregated weighted IVFS decision matrix can be obtained based on (2.8).

*Step 11: Determine positive-ideal solution and negative-ideal solution*

According to SVNS theory and the principle of classical TOPSIS method, SVNS-PIS and SVNS-NIS can be defined as below [21]:

$$\rho^+ = (a_j^+, b_j^+, c_j^+) \tag{3.17}$$

$$\rho^- = (a_j^-, b_j^-, c_j^-) \tag{3.18}$$

; where $\rho^+$ is the PIS and $\rho^-$ is the NIS and

$$a_j^+ = \begin{pmatrix} \max_i a_j, & if\ j \in G_1 \\ \min_i a_j, & if\ j \in G_2 \end{pmatrix} \qquad a_j^- = \begin{pmatrix} \max_i a_j, & if\ j \in G_2 \\ \min_i a_j, & if\ j \in G_1 \end{pmatrix}$$

$$b_j^+ = \begin{pmatrix} \max_i b_j, & if\ j \in G_2 \\ \min_i b_j, & if\ j \in G_1 \end{pmatrix} \qquad b_j^- = \begin{pmatrix} \max_i a_j, & if\ j \in G_1 \\ \min_i a_j, & if\ j \in G_2 \end{pmatrix}$$

$$c_j^+ = \begin{pmatrix} \max_i c_j, & if\ j \in G_2 \\ \min_i c_j, & if\ j \in G_1 \end{pmatrix} \qquad c_j^- = \begin{pmatrix} \max_i a_j, & if\ j \in G_1 \\ \min_i a_j, & if\ j \in G_2 \end{pmatrix}$$

For IVFS approach, however, the IVFS-PIS and IVFS-NIS could be defined as [26]:

$$\rho^+ = [(1,1); 1; (1,1)] \tag{3.17}$$

$$\rho^- = [(0,0); 0; (0,0)] \tag{3.18}$$

*Step 12: Calculate the Euclidian distance measures from SVN positive-ideal solution and SVN negative-ideal solution, the closeness coefficient(CC) and rank the alternatives*

Based on function (2.1), (2.2), and (2.3), the closeness coefficient (CC) of the alternatives are obtained and the list of preference are generated according to descending order for SVNS approach.

For IVFS approach, the Euclidian Distance could be calculated based on the following functions [26]:

$$D_{i1}^+ = \sum_j \sqrt{\frac{1}{3}[\left(a_{ij} - 1\right)^2 + \left(b_{ij} - 1\right)^2 + \left(b'_{ij} - 1\right)^2} \tag{3.19}$$

$$D_{i2}^+ = \sum_j \sqrt{\frac{1}{3}[\left(a'_{ij} - 1\right)^2 + \left(b'_{ij} - 1\right)^2 + \left(b_{ij} - 1\right)^2} \tag{3.20}$$

$$D_{i1}^- = \sum_j \sqrt{\frac{1}{3}[\left(a_{ij} - 0\right)^2 + \left(b_{ij} - 0\right)^2 + \left(b'_{ij} - 0\right)^2} \tag{3.21}$$

$$D_{i2}^- = \sum_j \sqrt{\frac{1}{3}[\left(a'_{ij} - 0\right)^2 + \left(b'_{ij} - 0\right)^2 + \left(b_{ij} - 0\right)^2} \tag{3.22}$$

The Closeness Coefficient for IVFS could be obtained by:

$$RC_1 = \frac{D_{i2}^-}{D_{i2}^+ + D_{i2}^-}, \qquad RC_2 = \frac{D_{i1}^-}{D_{i1}^+ + D_{i1}^-} \tag{3.23}$$

$$\mathrm{RC}_i^* = \frac{RC_1 + RC_2}{2} \tag{3.24}$$

The following flow diagram shows the steps of our MCDA algorithm:

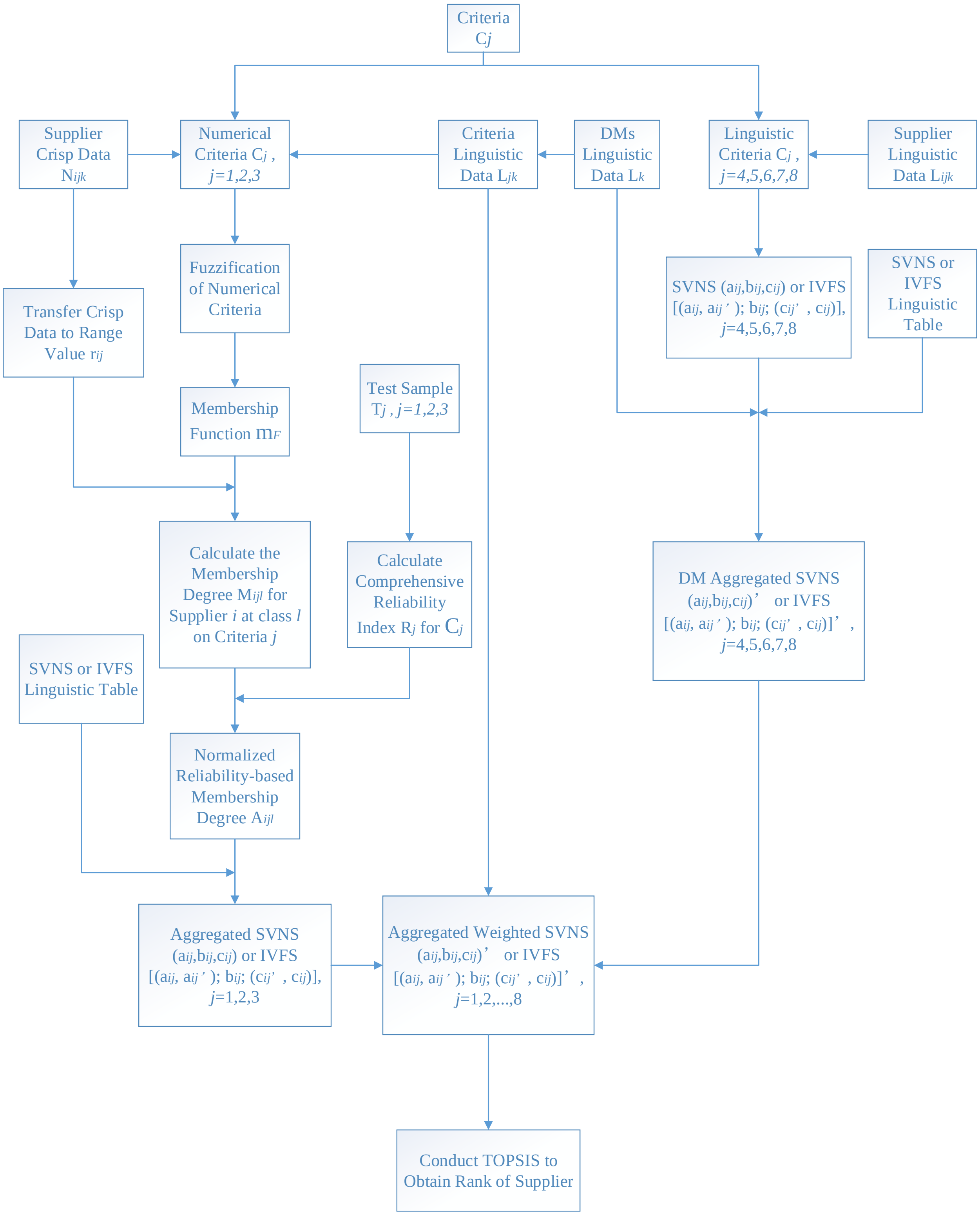


Figure 6. Framework of the Proposed MCDA algorithm.

# 4. Numerical Example

We randomly generated a data set, archived in appendix A to test the effectiveness of the proposed algorithm. We assumed that 10 decision makers (DM) have been appointed to evaluate 8 alternative suppliers with respect to 8 performance evaluation criteria that were discussed in section 2.7.

### 4.1 Result Analysis

The preferential ranking scores of the several alternative suppliers generated by the proposed algorithm using SVNS and IVFS approaches are presented in Table 9 and Table 10. A comparative analysis of the ranking score obtained in these two approaches are presented in Figure 7. We found that the final ranks of the alternative suppliers are almost same, and supplier 3 is selected as the optimal one in both SVNS and IVFS approaches, showing the robustness of the proposed decision-making algorithm.

Table 9. Ranking of the Suppliers.

SVNS Approach

| Supplier | d+ | d- | cc | Ranking |
|---|---|---|---|---|
| $S_1$ | 0.447 | 0.52 | 0.538 | 3 |
| $S_2$ | 0.656 | 0.409 | 0.384 | 8 |
| $S_3$ | 0.364 | 0.783 | 0.683 | 1 |
| $S_4$ | 0.639 | 0.476 | 0.427 | 6 |
| $S_5$ | 0.565 | 0.607 | 0.518 | 4 |
| $S_6$ | 0.644 | 0.512 | 0.443 | 5 |
| $S_7$ | 0.346 | 0.675 | 0.661 | 2 |
| $S_8$ | 0.617 | 0.428 | 0.409 | 7 |

IVFS Approach

| Supplier | $d_1^+$ | $d_2^+$ | $d_1^-$ | $d_2^-$ | $RC_1$ | $RC_2$ | RC | Ranking |
|---|---|---|---|---|---|---|---|---|
| $S_1$ | 3.5 | 4.3 | 4.3 | 5 | 0.5 | 0.4 | 0.456 | 3 |
| $S_2$ | 5.3 | 4.7 | 3.1 | 3.9 | 0.5 | 0.4 | 0.409 | 7 |
| $S_3$ | 4.2 | 3.7 | 5.4 | 4.3 | 0.6 | 0.5 | 0.546 | 1 |
| $S_4$ | 3.4 | 4.5 | 4.2 | 5.1 | 0.5 | 0.4 | 0.442 | 6 |
| $S_5$ | 5.2 | 8.2 | 3.5 | 8.2 | 0.5 | 0.4 | 0.451 | 4 |
| $S_6$ | 5.2 | 5.2 | 3.4 | 5.4 | 0.5 | 0.4 | 0.45 | 5 |
| $S_7$ | 4.5 | 3.9 | 4 | 5.2 | 0.6 | 0.5 | 0.521 | 2 |
| $S_8$ | 5.5 | 4.9 | 2.9 | 3.6 | 0.4 | 0.3 | 0.385 | 8 |

Table 10. Relationship between the Suppliers and the Criteria.

Relationship Between the Suppliers and the Criteria

| Supplier | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ |
|---|---|---|---|---|---|---|---|---|
| $S_1$ | P | N | N | N | P | N | N | P |
| $S_2$ | P | N | P | P | N | N | N | P |
| $S_3$ | P | P | N | P | N | N | P | P |
| $S_4$ | N | P | N | P | N | P | P | P |
| $S_5$ | P | P | P | P | N | N | P | N |
| $S_6$ | P | N | N | P | N | N | N | N |
| $S_7$ | P | N | P | P | P | N | P | P |
| $S_8$ | N | P | P | N | P | P | P | N |

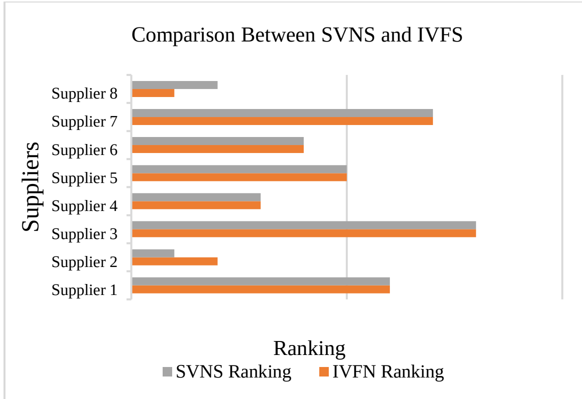


Figure 7. Comparison between SVNS and IVFN.

Given the fact that performance of the candidate supplier(s) may differ on different criteria, the change in the importance of the criteria would change the overall performance of a candidate supplier concerning all the criteria. The relationship between the performance of the resilient suppliers and the criteria are summarized in Table 10 wherein P and N to positive and Negative association. A positive association signifies that the resiliency property of the suppliers would benefit from the increase of the weight of that criterion, implying that the CC of the supplier would be higher if the importance of the criterion is increased. More conclusively, a positive association implies that a supplier possesses a good resilience performance on this criterion. A negative association between the supplier's performance and importance of the criteria has an opposite meaning.

As previously mentioned, the membership functions are modified using the reliability index, we further compared the results of the Reliability-modified model and the original model and presented the outcome in Figure 9. The result shows that the consideration of the reliability has slightly changed the CC of the suppliers, concluding that the consideration of the reliability-based membership function influences the overall preferential ranking of the alternative suppliers.

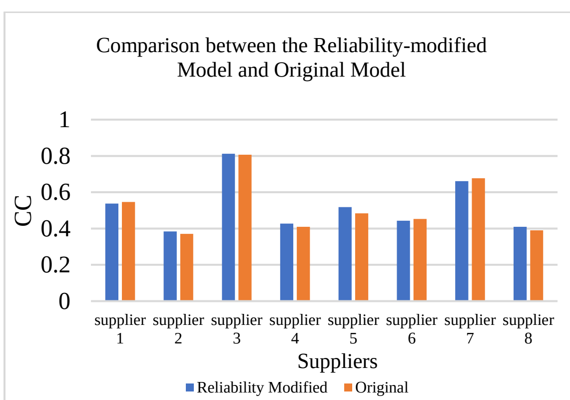


Figure 8. Comparison Between the Reliability-modified Model and Original Model

In addition, to further validate the importance of considering reliability-based membership function in MCDA framework, we adopt the method proposed in [13] to perform another set of comparative analysis. Because the existing method do not consider multiple decision makers, we only extract the data of DM1 from our original data set to be consistent in the comparative analysis. Besides, crisp data 1 to 9 are assigned to linguistic terms from VB to EG to replace the SVNS. The comparison of the result of our proposed MCDA model and the classical model are presented in Figure 10. Apart from the three suppliers (1, 3 & 7), we observed significant changes in the ranking score of the candidate suppliers while adopting the reliability based SVNS approach as compared to traditional MCDA approach.

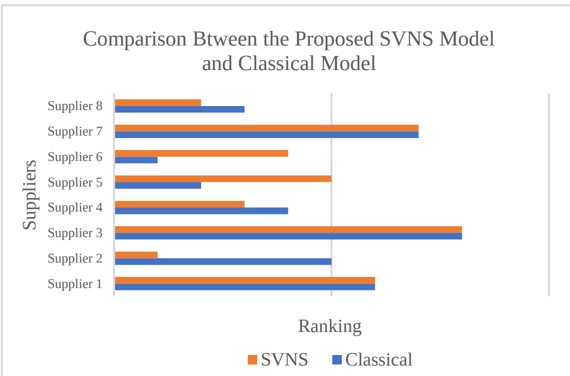


Figure 9. Comparison for Original Model.

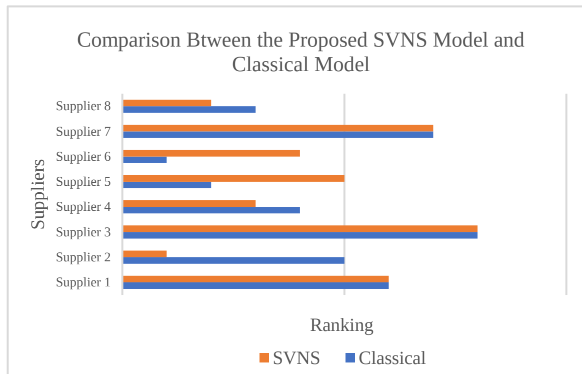


Figure 10. Comparison for Classical Model.

### 4.2 Sensitivity Analysis

In real world, the requirements of the decision-makers who need to select the optimal supplier differs significantly due to their diverse preferences on several criteria. For example, some of the decision-makers may care more about buffer capacity while the others' satisfaction would be fulfilled only when the alternative shows a superior performance on responsiveness. That is, the ranking of the supplier(s) may change while different weights are assigned to different criteria. To test whether our proposed algorithm is capable of explaining this, we conduct a sensitivity analysis with respect to the variation in the weight of criteria to observe the corresponding change in the CC and the final list of preference.

The weight in the form of SVNS is summarized in Table 3. For SVNS, the higher the importance of a criterion, the larger the truth value. So, we can adopt the truth value to represent the SVNS weight to do the sensitivity analysis. Considering C7 as example, the SVNS for $C_7$ is (0.34, 0.76, 0.79) and assuming the representative weight for $C_j$ is $\alpha_j$, then we have $\alpha_7 = 0.34$. To check the impact of the value of $\alpha_7$ on the final ranking score (CC), we would slightly change the value of $\alpha_7$. Because the weights are calculated from the original linguistic data based on Table 1, we can gradually change the original linguistic data on $C_7$ to obtain the $\alpha_7$ we desired. The original linguistic data for $C_7$ and corresponding value of $\alpha_7$ could be summarized as follows:

Table 11. Original Linguistic Data for Criteria 7 ($C_7$).

| Data Set | Original Linguistic Data for $C_7$ | | | | | | | | | | $\alpha_7$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| DMs | $DM_1$ | $DM_2$ | $DM_3$ | $DM_4$ | $DM_5$ | $DM_6$ | $DM_7$ | $DM_8$ | $DM_9$ | $DM_{10}$ | |
| Original Data Set | UI | UI | VUI | UI | VUI | VUI | M | M | UI | UI | 0.34 |
| Data Set 1 | VUI | VUI | VUI | VUI | VUI | VUI | VUI | VUI | VUI | VUI | 0.1 |
| Data Set 2 | VUI | VUI | VUI | VUI | VUI | VUI | UI | UI | UI | UI | 0.2 |
| Data Set 3 | VUI | VUI | VUI | UI | UI | VUI | M | M | UI | UI | 0.3 |
| Data Set 4 | M | M | UI | UI | VUI | VUI | M | M | UI | UI | 0.4 |
| Data Set 5 | M | M | UI | M | UI | UI | I | I | UI | UI | 0.5 |
| Data Set 6 | I | I | UI | UI | UI | UI | I | I | UI | M | 0.6 |
| Data Set 7 | I | I | M | I | M | M | VI | I | M | M | 0.7 |
| Data Set 8 | VI | VI | I | I | UI | M | VI | VI | I | I | 0.8 |
| Data Set 9 | VI | VI | VI | VI | VI | VI | VI | VI | VI | VI | 0.9 |

While we change the value of $\alpha_7$, the SVNS weight of other criteria would remain the same based on (2.13). However, as the original performance measurement will be multiplied by the weight to get the weighted performance measurement, the suppliers who have better performance on $C_7$ would benefit from the increased weight, leading to a higher CC which, eventually will change the preferential order of the alternative suppliers.

Fig 7 shows the sensitivity analysis on $C_7$. To make it easy to understand, we only pick supplier 3 and supplier 7 as they have the highest CC.

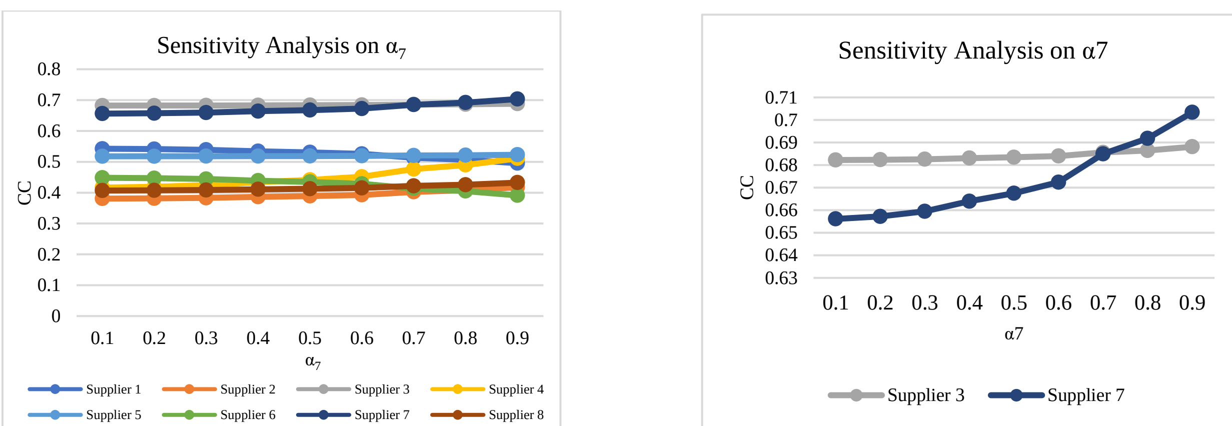


Figure 11. Sensitivity Analysis on α7.

We found that, when $\alpha_7 < 0.7$, the optimal supplier is supplier 3; when $\alpha_7 \geq 0.7$,supplier 3 loses its priority over supplier 7. We must mention that, as the $\alpha_i$ are independent from each other, we only focus on one $\alpha_i$ at one time. Particularly, in doing the sensitivity analysis against one criteria, only the weight of that criteria is adjusted while keeping the weight of other criteria constant. In addition, because the weight is in the form of SVNS, $\sum_i \alpha_j \neq 1$. But we could do the sensitivity analysis on every $\alpha_i$ separately to check their influence on the final rank. The results are summarized in Table 12.

Table 12. Result of the Sensitivity Analysis.

| $\alpha_j$ | Range | Optimal Supplier | Range | Optimal Supplier |
|---|---|---|---|---|
| $\alpha_1$ | (0.1,0.9) | $S_3$ | - | - |
| $\alpha_2$ | (0.1,0.9) | $S_3$ | - | - |
| $\alpha_3$ | (0.1,0.72) | $S_3$ | (0.72,0.9) | $S_7$ |
| $\alpha_4$ | (0.1,0.8) | $S_3$ | (0.8,0.9) | $S_7$ |
| $\alpha_5$ | (0.1,0.9) | $S_3$ | - | - |
| $\alpha_6$ | (0.1,0.75) | $S_3$ | (0.75,0.9) | $S_7$ |
| $\alpha_7$ | (0.1,0.7) | $S_3$ | (0.7,0.9) | $S_7$ |
| $\alpha_8$ | (0.1,0.75) | $S_3$ | (0.75,0.9) | $S_7$ |

## 5. Conclusion

Because of the limitation of the current fuzzy-based TOPSIS method applied in the resilient supplier selection problem, there is not existing approach that could provide a comprehensive way to evaluate the alternative suppliers with respect to numerical and linguistic criteria simultaneously. We adapted and extended SVNS and IVFS techniques to consider quantitative and linguistic evaluation criteria in our decision-making algorithm. To consider the unreliability of the information, we calculated reliability indices to modify the obtained membership functions to make them reliability adjusted. With the help of reliability-based membership degree, the crisp data on numerical criteria are transferred to aggregated SVNS or IVFS decision matrix, which are then combined with the decision matrix on linguistic criteria and ranked by the TOPSIS tool. The comparative results generated from these two approaches (SVNS and IVFS) verifies the effectiveness of our algorithm. We also perform a sensitivity analysis to show how the priority of an evaluation criterion impact the preference ranking of the suppliers. The developed MCDA algorithm is an effective and reliable tool for supply chain stakeholders to evaluate multiple suppliers considering several conflicting criteria with imprecise and unreliable decision relevant information. In the future, we will try to find a candidate component in IVFS so that we could conduct a sensitivity analysis in IVFS approach as well. In addition, we will further extend this current work to develop a method that could optimize the weight of decision maker while aggregating the numerical data set.

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