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Semantic Risk Analysis Based on Single-Valued Neutrosophic Sets

LINFENG GOU [1] AND MEIJUAN WANG [2]

[1]School of Power and Energy, Northwestern Polytechnical University, Xi'an 710072, China
[2]School of Electronics and Information, Northwestern Polytechnical University, Xi'an 710072, China

Corresponding author: Linfeng Gou (goulinfengnwpu@126.com)

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ABSTRACT Fuzzy risk analysis is diffusely applied in risk assessment of components by the semantic model. Due to the fuzzy characteristic in the process of fuzzy risk analysis, analysis parameters are imprecise and vague. Therefore, the determination of the risk of failure is challenging part of fuzzy risk analysis with existing methods. Hence, in this paper, a semantic risk analysis method based on the technique for order performance by similarity to ideal solution (TOPSIS) under a single-valued neutrosophic set (SVNS) is presented. First, a five-member linguistic term set is introduced and these linguistic terms are expressed in terms of the generalized trapezoidal fuzzy numbers. Then, the linguistic term is transformed into the SVNS and generated SVNS is fused by single-valued neutrosophic prioritized weighted average (SVNPWA) operator. On this basis, the TOPSIS approach is used to obtain the final rank to ascertain future risk. Finally, a fuzzy risk analysis example is conducted to illustrate the effectiveness of the proposed method. Further, the out-performance of the proposed method is illustrated in comparisons to the existing methods.

INDEX TERMS Fuzzy risk analysis, linguistic term, SVNS, SVNPWA operator, TOPSIS.

I. INTRODUCTION

Fuzzy risk analysis plays a significant role in risk assessment of components to estimate risk of failure. In the process of fuzzy risk analysis, people sometimes feel more convenient to express their preferences by semantic model instead of quantitative form [1]. In addition, analysis parameters are imprecise and vague due to fuzzy characteristic. Therefore, the semantic model has gained popularity among the researchers, and it is an effective way to model fuzzy numbers that support the semantics of the linguistic terms [2]. To deal with fuzzy risk analysis problems, the risk of component is assessed by linguistic terms and their equivalent fuzzy numbers. Schmucker [3] first introduced a risk evaluation way based on sub-components in production system by using two parameters, which are probability of failure and severity of loss. And the parameters are expressed as linguistic terms. Generally, it happens that the linguistic term is converted to the corresponding fuzzy number. For example, a nine-member set of linguistic terms was proposed by Zhang [4], and each linguistic term is indicated by a generalized trapezoidal fuzzy number.

A number of theories have been developed on fuzzy risk analysis, such as Bayes theory [5]–[7], Dempster-Shafer theory of evidence [8]–[13], fuzzy set theory [14]–[19], rough sets [20]–[22], intuitionistic fuzzy sets [23]–[25], D numbers [26] and Z numbers [27]–[29]. However, neutrosophic set is rarely used in fuzzy risk analysis. Hence, the single-valued neutrosophic sets are applied in fuzzy risk analysis in this paper. The neutrosophic logic and neutrosophic set (NS), first proposed by Smarandache in 1998, which clearly refers to neutral knowledge as independent component [30]. The NS is characterized by three membership functions which describe the function of truth, indeterminacy and falsity [31]. And the three functions assume values lie in the non-standard interval of $]0^-, 1^+[$. Smarandache [30] in 1998 and Haibin *et al.* [32] in 2010 clearly pointed out that the non-standard interval is impractical to apply in realistic problems. In view of this, Smarandache [30] and Haibin *et al.* [32] introduced the conceptualization of single-valued neutrosophic set (SVNS), which is defined in the standard unit interval of [0, 1]. As three membership values in [0, 1], it is able to seize the intuitiveness of the process of allocating membership

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values [33]. Subsequently, studies of SVNS have focused on defining operations, correlation coefficient measures [34]–[36], similarity measures [37]–[41], distance measures [42]–[45] and aggregation operators [46]–[54]. For instance, Liu [46] introduced a single-valued neutrosophic number-weighted averaging (SVNNWA) operator and a single-valued neutrosophic number-weighted geometric (SVNNWG) operator based on Archimedean t-conorm and t-norm (ATT). Furthermore, Garg *et al.* [49] extended Muirhead mean (MM) aggregation operator, and then developed single-valued neutrosophic (SVN) prioritized MM (SVNPMM) and SVN prioritized dual MM (SVNPDMM).

In general, fuzzy risk analysis is investigated based on either similarity measures or ranking. To deal with complicated problems, fuzzy risk analysis has been applied based on both similarity measures and ranking of fuzzy numbers [55]. The similarity measures are commonplace method which have attracted many researchers to measure the degree of similarity in fuzzy risk analysis. Based on centers-of-gravity of membership and nonmembership functions, Zhou *et al.* [56] introduced a weighted similarity measure between trapezoidal intuitionistic fuzzy numbers. Patra and Mondal [57] developed a similarity measure using geometric distance, area and height of two trapezoidal valued fuzzy numbers. Khorshidi and Nikfalazar [58] proposed a new similarity measure between generalized trapezoidal fuzzy numbers using geometric distance, distance of COG, area difference, height difference, and perimeter ratio. Based on the geometric distance, radius of gyration points and the heights of the upper and the lower generalized fuzzy numbers of the interval-valued fuzzy numbers, Chutia and Rituparna [59] proposed a new similarity measure method. With the help of geometric distance, area and height, Patra and Mondal [57] proposed a similarity measure method between trapezoidal fuzzy numbers. Some ranking methods have also been studied by some researchers. Chen *et al.* [60] calculated the areas on the positive side, the negative side and the centroid of the generalized fuzzy numbers to evaluate the ranking scores of the generalized fuzzy numbers. Madhuri *et al.* [61] proposed a new ranking for generalized trapezoidal fuzzy numbers based on circumcentre of centroids. The decision maker optimistic attitude and the index of modality were considered while ranking fuzzy numbers, Shankar *et al.* [62] proposed a ranking method based on orthocenter of centroids. A simple point-wise arithmetic operation was applied, Ramli *et al.* [63] introduced the Jaccard ranking index with algebraic product t-norm in dealing with fuzzy risk analysis problem. As the ranking method mentioned in literature, most of methods cannot be applied to crisp numbers which are a special case of fuzzy numbers. And some methods are inconsistent with human intuition and shows bad results in many situations. Furthermore, some method cannot fast obtain the suitable risk calculating results when dealing with complex risk analysis issues.

From the above analysis, prior studies rarely employed SVNS to deal with fuzzy risk analysis problems and some drawbacks in the existing ranking methods. In order to solve those problems, this paper creates a semantic risk analysis method based on single-valued neutrosophic sets, using the technique for order performance by similarity to ideal solution (TOPSIS) ranking method that have been applied in order to estimate risk of failure. A concept of SVNS developed by Haibin *et al.* [32] is introduced in this paper to capture the intuitiveness of the process of assigning membership values. The truth-membership function, the indeterminacy-membership function and the falsity-membership function of SVNS are fuzzy values rather than exact numbers. This gives SVNS the ability to handle uncertainty, imprecision, incompletion and indetermination of information. A five-member linguistic terms set is introduced in this paper, and these linguistic terms are associated with the generalized trapezoidal fuzzy numbers. In the case of considering the single-valued neutrosophic value, the SVNSs are generated by the linguistic terms. Then, the generated SVNSs are fused by single-valued neutrosophic prioritized weighted average (SVNPWA) operator. Afterwards, the risk of failure can be determined by the application of TOPSIS method. Although, the proposed method is entirely based on existing concepts, yet excellent results are being seen in comparisons with the existing method. The proposed method not only overcomes the drawbacks of the existing methods but also better expresses uncertain information to improve the reliability of fuzzy risk analysis.

The rest of this paper is organized as follows. Section II briefly introduces basic concepts of generalized trapezoidal fuzzy numbers, SVNS and the (SVNPWA) operator as well as some operations for SVNS. In Section III, a five-member linguistic terms set is introduced and procedures of the proposed method are illustrated in detail. In Section IV, the proposed method is applied to deal with fuzzy risk analysis problems and comparison analysis are given to illustrate the effectiveness and feasibility of the proposed methodology. Finally, Section V gives the concluding remarks.

II. PRELIMINARIES

A. GENERALIZED TRAPEZOIDAL FUZZY NUMBERS

Chen [64], [65] proposed the concept of generalized trapezoidal fuzzy numbers, defined as follows:

Definition 1: Let A be a generalized trapezoidal fuzzy number, $A = (a_1, a_2, a_3, a_4, \omega_A)$, where a_1, a_2, a_3 and a_4 are real values, ω_A denotes the height of the generalized trapezoidal fuzzy number A, and $0 \leq \omega_A \leq 1$, as shown in Fig.1.

When $\omega_A = 1$, the generalized trapezoidal fuzzy number A becomes a traditional fuzzy number, denoted as $A = (a_1, a_2, a_3, a_4)$. When $a_1 < a_2 = a_3 < a_4$, the generalized trapezoidal fuzzy number A becomes a triangular fuzzy number. When $a_1 = a_2$ and $a_3 = a_4$, the generalized trapezoidal fuzzy number A becomes a crisp interval fuzzy number. When $a_1 = a_2 = a_3 = a_4$ and $\omega_A = 1$,

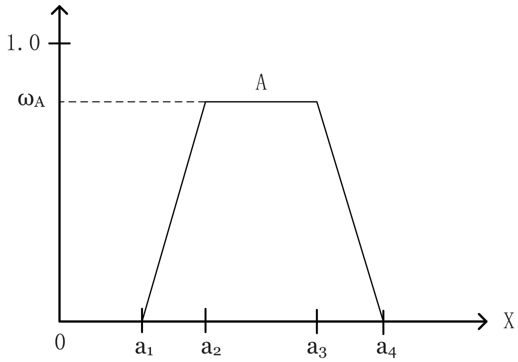

FIGURE 1. **A generalized trapezoidal fuzzy number A.**

the generalized trapezoidal fuzzy number A becomes a crisp value.

B. THE SINGLE-VALUED NEUTROSOPHIC SET

By extending neutrosophic set, Haibin *et al.* [32] introduced the definition of the single-valued neutrosophic set as follows:

Definition 2: Let X be a finite set, with a element of X denoted by x. A single-valued neutrosophic set P on X is:

$$P = \{\langle x, T_P(x), I_P(x), F_P(x)\rangle \mid x \in X\}, \tag{1}$$

where $T_P(x), I_P(x)$ *and* $F_P(x)$ are the truth-membership function, the indeterminacy-membership function and the falsity-membership function, respectively. And for all $x \in X$, clearly satisfy condition:

$$\begin{aligned} &0 \leq T_P(x), \quad I_P(x), \quad F_P(x) \leq 1, \\ &0 \leq T_P(x) + I_P(x) + F_P(x) \leq 3. \end{aligned} \tag{2}$$

For convenience, a single-valued neutrosophic set P can be denoted briefly as $x = (T_x, I_x, F_x)$.

In addition, Nancy and Garg [66] proposed the score function S of the single-valued neutrosophic number, as follows:

$$S(x) = \frac{1 + (T_x - 2I_x - F_x)(2 - T_x - F_x)}{2}. \tag{3}$$

Based on the above score function, Nancy and Garg [66] proposed a compare method for the single-valued neutrosophic numbers. For any two single-valued neutrosophic numbers $x = (T_x, I_x, F_x)$ and $y = \left(T_y, I_y, F_y\right)$, if $S(x) > S(y)$ then $x > y$.

Majumdar and Samanta [67] defined Euclidean distance of the single-valued neutrosophic sets:

Definition 3: Let $P = \{\langle x_1, T_P(x_1), I_P(x_1), F_P(x_1)\rangle, \ldots, \langle x_n, T_P(x_n), I_P(x_n), F_P(x_n)\rangle\}$ and $Q = \{\langle x_1, T_Q(x_1), I_Q(x_1), F_Q(x_1)\rangle, \ldots, \langle x_n, T_Q(x_n), I_Q(x_n), F_P(x_n)\rangle\}$. Then the Euclidean distance between two SVNSs P and Q can be defined as follows:

$$d(P, Q) = \sqrt{\sum_{i=1}^{n}\left\{\begin{array}{c}\left(T_P(x_i) - T_Q(x_i)\right)^2 + \left(I_P(x_i) - I_Q(x_i)\right)^2 \\ + \left(F_P(x_i) - F_Q(x_i)\right)^2\end{array}\right\}}, \tag{4}$$

and the normalized Euclidean distance between two SVNSs P and Q can be defined as follows:

$$d^n(P, Q) = \sqrt{\frac{1}{3n}\sum_{i=1}^{n}\left\{\begin{array}{c}\left(T_P(x_i) - T_Q(x_i)\right)^2 + \left(I_P(x_i) - I_Q(x_i)\right)^2 \\ + \left(F_P(x_i) - F_Q(x_i)\right)^2\end{array}\right\}}. \tag{5}$$

C. THE SVNPWA OPERATOR

The integration operator of the single-valued neutrosophic set is given as follows [68]:

Definition 4: For a collection of SVNSs $P_i = \{x_i, T_P(x_i), I_P(x_i), F_P(x_i)\}(i = 1, 2, \ldots, n)$, the SVNPWA Operator is defined as follows:

$$SVNPWA(P_1, P_2, \ldots, P_n) = \left(\begin{array}{c} 1 - \prod_{i=1}^{n}\left(1 - T_P(x_i)\right)^{\frac{H_i}{\sum_{i=1}^{n} H_i}}, \prod_{i=1}^{n}\left(I_P(x_i)\right)^{\frac{H_i}{\sum_{i=1}^{n} H_i}}, \\ \prod_{i=1}^{n}\left(F_P(x_i)\right)^{\frac{H_i}{\sum_{i=1}^{n} H_i}} \end{array}\right). \tag{6}$$

where $H_1 = 1$ and $H_i = \prod_{k=1}^{i-1} S(P_i)(i = 2, 3, \cdots, n)$.

III. THE PROPOSED METHOD

In the following, a semantic risk analysis method based on SVNSs and TOPSIS ranking that has been introduced to deal with the fuzzy risk analysis problem. Schmucker [3] first discussed the risk analysis problem under fuzzy environment. Here, a component C is built-up by n sub-components C_i, $(i = 1, 2, \ldots, n)$. Now, each sub-components C_i is evaluated by two evaluating items probability of failure and severity of loss. As the probabilistic values of these items are imprecise and vague due to fuzzy characteristic, so these items are more precisely assessed by linguistic terms. The linguistic term R_i denotes the probability of failure of the sub-component C_i and the linguistic term W_i denotes the severity of loss of the sub-component C_i. On this basis, the structure of a fuzzy risk analysis is shown in Fig. 2 [3]. Then the values of linguistic items are represented by the generalized fuzzy numbers. In this paper, a 5-member linguistic term set is used to represent the linguistic terms. Each linguistic term in the 5-member linguistic term set is corresponding to a generalized trapezoidal fuzzy number, as shown in Table 1. Fig. 3 illustrates five trapezoidal fuzzy numbers provided in Table 1.

Suppose that there is a component C contains n sub-components $C_1, C_2, \ldots$, and C_n. And suppose that each sub-component is evaluated by two evaluating items probability of failure R_{ij} and severity of loss W_{ij}, where i = 1, 2, . . . , n, on behalf of n sub-components. In addition, j = VL, L, M, H, VH, respectively, on behalf of five members linguistic term: very-low, low, medium, high and very-high. For example, R_{1VL} means linguistic term very-low of the 1-th sub-component. The R_{ij} and W_{ij} are linguistic terms are shown

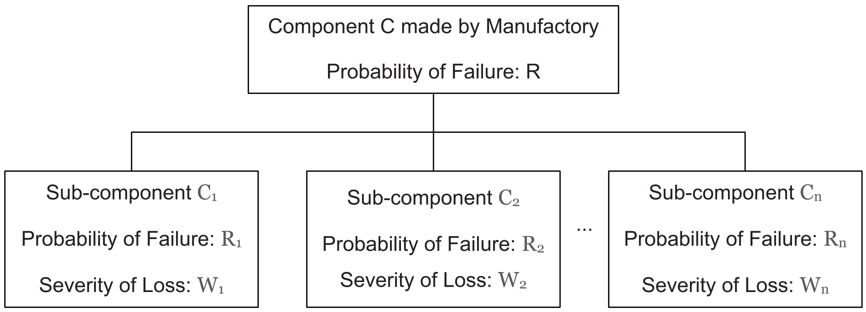

FIGURE 2. **Structure of fuzzy risk analysis [3].**

TABLE 1. **A 5-member linguistic term set.**

Linguistic terms	Generalized trapezoidal fuzzy numbers
Very-low	(0, 0, 0.1, 0.17; 1.0)
Low	(0.09, 0.14, 0.28, 0.37; 1.0)
Medium	(0.29, 0.36, 0.54, 0.62; 1.0)
High	(0.56, 0.64, 0.78, 0.87; 1.0)
Very-high	(0.85, 0.91, 1.0, 1.0; 1.0)

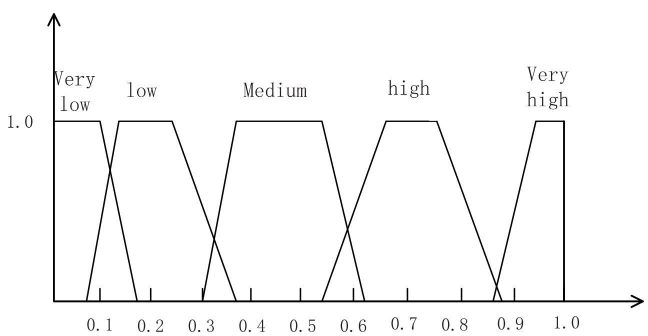

FIGURE 3. **Five trapezoidal fuzzy numbers.**

in Table 1. The flowchart of the proposed method is presented as Fig. 4. The proposed method for dealing with fuzzy risk analysis is now presented as follows:

(i) The linguistic terms R_{ij} and W_{ij} are transformed to SVNSs. The linguistic terms and their equivalent generalized trapezoidal fuzzy numbers $A_{ij} = (a_{1ij}, a_{2ij}, a_{3ij}, a_{4ij})$ are shown in Table 1. A SVNS $x_{ij} = (T_{xij}, I_{xij}, F_{xij})$ is characterized by the truth-membership function, the indeterminacy-membership function and the falsity-membership function. Three functions are generally determined by practical experience and fuzzy statistic. Based on the characteristics of SVNS and the generalized trapezoidal fuzzy number, Eq. (7) is proposed to obtain three functions of SVNS, as follows:

$$T_{xij} = \frac{a_{2ij} + a_{3ij}}{2},$$
$$I_{xij} = 1 - \left(a_{4ij} - a_{1ij}\right),$$
$$F_{xij} = 1 - T_{xij}. \tag{7}$$

(ii) Due to the complexity of components and instability of working conditions, the fuzzy risk analysis

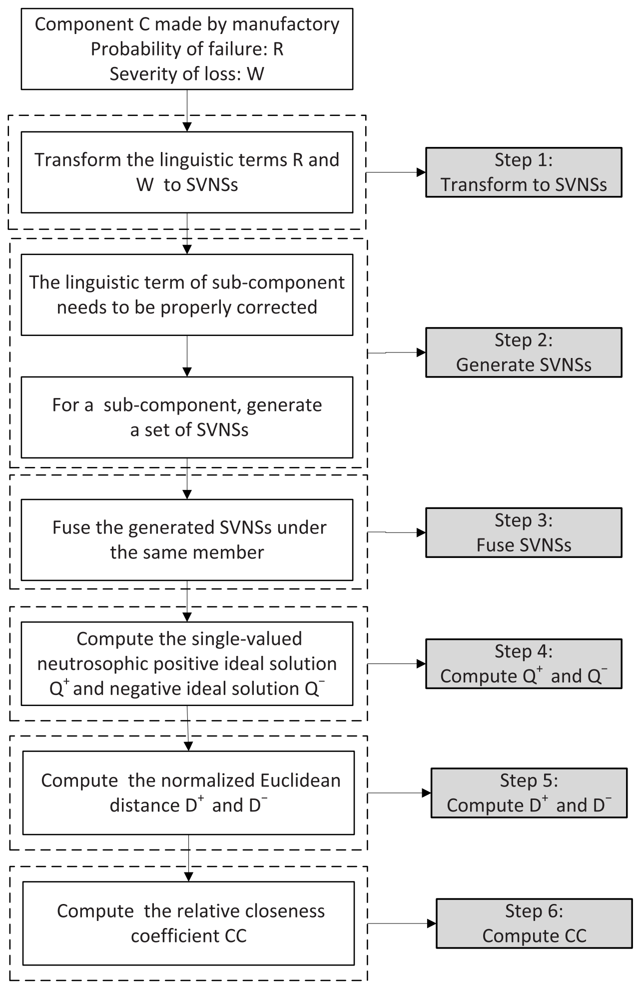

FIGURE 4. **The flowchart of the proposed method.**

is insufficient. And evaluation parameters involved are imprecise owing to its nature in many situation. The sub-component is evaluated by probability of failure and severity of loss, which are expressed as linguistic terms. The linguistic terms are used to quantify the associated uncertainty and it is difficult to make accurate judgment with linguistic terms. Therefore, when conducting a risk assessment of a sub-component, appropriate correction of the linguistic term can better express uncertain information. For the evaluating item probability of failure of a sub-component, the corresponding falsity-membership function of SVNS are equally divided into two adjacent members as their the truth-membership functions. In this paper, without loss of generality, the indeterminacy-membership function of the adjacent members are 0.5. And the falsity-membership function of the adjacent members are obtained by the third formula of Eq. (7). The newly SVNSs are considered as risk assessment of sub-component. Hence, there are three members of evaluation linguistic terms for sub-components. It can express the uncertainty more accurately and improve the accuracy of fuzzy risk analysis. For example, the linguistic value of R_2 of sub-component C_2 is " low ", the corresponding SVNS $x_{2L} = (0.14, 0.81, 0.86)$ is gained by Eq. (7). From Table 1, it can be easily seen that the two adjacent members to " Low " are " Very-low " and " Medium ". Then, the SVNSs of " Very-low " member and " Medium " member are obtained, respectively $x'_{2VL} = (0.43, 0.5, 0.57)$ and $x'_{2M} = (0.43, 0.5, 0.57)$. Therefore, the linguistic value of W_2 are " low ", " Very-low " and " Medium ".

(iii) Fuse the generated SVNSs under the same member and fusion result $x_j = (T_{xj}, I_{xj}, F_{xj})$ will be obtained by using the SVNPWA operator (Eq. (6)). For example, the generated SVNSs $x_{1M} = (T_{x1M}, I_{x1M}, F_{x1M})$, $x_{2M} = (T_{x2M}, I_{x2M}, F_{x2M})$, $x_{3M} = (T_{x3M}, I_{x3M}, F_{x3M})$ are gained under the linguistic value " Medium ", the fusion process is shown as follows:

$$x_3 = SVNPWA(x_{1M}, x_{2M}, x_{3M}) = \left(\begin{array}{c} 1 - \prod_{i=1}^{3} (1 - T_{xiM})^{\frac{H_i}{\sum_{i=1}^{3} H_i}}, \prod_{i=1}^{3} (I_{xiM})^{\frac{H_i}{\sum_{i=1}^{3} H_i}}, \\ \prod_{i=1}^{3} (F_{xiM})^{\frac{H_i}{\sum_{i=1}^{3} H_i}} \end{array} \right). \quad (8)$$

where $H_1 = 1$, $H_2 = S(x_{1M})$ and $H_3 = S(x_{1M}) \times S(x_{2M})$. And $S(x_{iM})$ can be calculated by Eq. (3).

(iv) Compute the single-valued neutrosophic positive ideal solution (SVNPIS) and single-valued neutrosophic negative ideal solution (SVNNIS). Consider Q^+ and Q^- be the SVNPIS and SVNNIS. Then, Q^+ and Q^- can be defined as follows:

$$Q^+ = (\max(T_{xij}), \min(I_{xij}), \min(F_{xij}))$$
$$Q^- = (\min(T_{xij}), \max(I_{xij}), \max(F_{xij})) \quad (9)$$

(v) Compute the normalized Euclidean distance from $x_j = (T_{xj}, I_{xj}, F_{xj})$ to SVNPIS and SVNNIS. In actual working environment, the evaluation linguistic terms are inequacy. Therefore, the weight of each linguistic term is not counted. Based on this situation, the statistical mean method is usually applied to determine the weight of linguistic term of component, that is, the weight of linguistic term is balanced. In this paper, without loss of generality, the weight of linguistic term is denoted as: $\omega = (\omega_1, \omega_2, \omega_3, \omega_4, \omega_5) = \left(\frac{1}{5}, \frac{1}{5}, \ldots, \frac{1}{5}\right)$. The normalized Euclidean distance D^+ from component x_j to the SVNPIS can be obtained based on Eq. (5):

$$D_j^+(x_j, Q^+) = \omega_j \times d^n(x_j, Q^+), \quad (10)$$

Similarly, the normalized Euclidean distance D^- of component x_j from the SVNNIS can be written as follows:

$$D_j^-(x_j, Q^-) = \omega_j \times d^n(x_j, Q^-). \quad (11)$$

(vi) Compute the closeness coefficient CC_j, based on measuring the extent which component x_j is close to the SVNPIS as well as far from the SVNNIS, simultaneously. The CC_j is defined as follows [69]:

$$CC_j = \frac{D_j^-(x_j, Q^-)}{D_{j\max}^-(x_j, Q^-)} - \frac{D_j^+(x_j, Q^+)}{D_{j\min}^+(x_j, Q^+)}. \quad (12)$$

where

$$D_{j\min}^+(x_j, Q^+) = \min D_j^+(x_j, Q^+),$$
$$D_{j\max}^-(x_j, Q^-) = \max D_j^-(x_j, Q^-). \quad (13)$$

It is obvious that $CC_j \leq 0$ (j = VL, L, M, H, VH), and the bigger the value of CC_j is, the greater the probability of risk member of component.

TABLE 2. Linguistic values of the evaluating items R_i and W_i of the three sub-components C_1, C_2 and C_3.

Sub-component C_i	Severity of loss	Probability of failure
C_1	Medium	Low
C_2	High	Medium
C_3	Low	Very-high

IV. APPLICATION IN FUZZY RISK ANALYSIS

A. A NUMERICAL EXAMPLE

This section illustrates the effectiveness of the proposed method by using the example of fuzzy risk analysis. Consider the structure of fuzzy risk analysis shown in Fig. 2, where the component C made by manufactory consists of three sub-components, C_1, C_2 and C_3. These sub-components are evaluated by linguistic term, shown in Table 2. In the following, the proposed method is applied to deal with the fuzzy risk analysis problem.

(i) Transform the linguistic values to SVNSs by Eq. (7). Taking severity of loss W_{2H} as an example, the generalized trapezoidal fuzzy number equivalent to W_{2H} is

TABLE 3. The corrected linguistic term of sub-component.

Sub-component C_i	Severity of loss W
C_1	W'_{1L} =(0.395,0.50,0.605) W_{1M} = (0.45,0.67,0.55) W'_{1H} = (0.395,0.50,0.605)
C_2	W'_{2M} = (0.275,0.50,0.725) W_{2H} = (0.71,0.69,0.29) W'_{2VH} = (0.275,0.50,0.725)
C_3	W'_{3VL} =(0.0225,0.50,0.9775) W_{3L} = (0.21,0.72,0.29) W'_{3M} =(0.0225,0.50,0.9775)

$A_{2H} = (0.56, 0.64, 0.78, 0.87)$ and part of the calculation procedures are as follows:

$$T_{x2} = \frac{a_2 + a_3}{2} = \frac{0.64 + 0.78}{2} = 0.71,$$
$$I_{x2} = 1 - (a_4 - a_1) = 1 - (0.87 - 0.56) = 0.69,$$
$$F_{x2} = 1 - T_{x2} = 1 - 0.71 = 0.29. \quad (14)$$

(ii) In order to better express uncertainty, the linguistic term of sub-component needs to be properly corrected. The corrected linguistic terms of sub-components are shown in Table 3. For example, the linguistic value of R for sub-component C_2 is " Medium ", the corresponding SVNS $x_{2M} = (0.45, 0.67, 0.55)$ is gained by Eq. (7). From Table 1, it can be easily seen that the two adjacent members to " Medium " are " Low " and " High ". Then, the SVNSs of " Low " member and " High " member are obtained, respectively $x'_{2L} = (0.275, 0.50, 0.725)$ and $x'_{2H} = (0.275, 0.50, 0.725)$. Therefore, the linguistic value of severity of loss are " Low ", " Medium " and " High ".

(iii) Fuse the generated SVNSs in Table 3 under the same member by Eq. (6). From Table 3, it can be seen that W'_{1L} and W_{3L} are the corresponding SVNSs of linguistic value "Low". W_{1M}, W'_{2M}, and W'_{3M} are the corresponding SVNSs of linguistic value "Medium". And W'_{1H} and W_{2H} are the corresponding SVNSs of linguistic value "High". The specific calculation processes are as follows:

$$x_{VL} = W'_{3VL} = (0.0225, 0.50, 0.9775),$$
$$x_L = SVNPWA(W'_{1L}, W_{3L}) = (0.4136, 0.4791, 0.5864),$$
$$x_M = SVNPWA(W_{1M}, W'_{2M}, W'_{3M}) = (1, 0, 0),$$
$$x_H = SVNPWA(W'_{1H}, W_{2H}) = (0.7058, 0.6857, 0.2942),$$
$$x_{VH} = W'_{2VH} = (0.2750, 0.50, 0.7250). \quad (15)$$

(iv) Compute the single-valued neutrosophic positive ideal solution Q^+ and single-valued neutrosophic negative ideal solution Q^- by Eq. (9), as follows:

$$Q^+ = (0.9550, 0.67, 0.0450),$$
$$Q^- = (0.21, 0.85, 0.79). \quad (16)$$

(v) In this paper, the weight of x_i (i = VL, L, M, H, VH) is denoted as: $\omega = (\omega_{VL}, \omega_L, \omega_M, \omega_H, \omega_{VH}) = (0.2, 0.2, 0.2, 0.2, 0.2)$. Then, the normalized Euclidean distance D_i^+ from x_i to the SVNPIS can be obtained by Eq. (10), as follows:

$$D_{VL}^+ (x_{VL}, Q^+) = \omega_{VL} \times d^n (x_{VL}, Q^+) = 0.7677,$$
$$D_L^+ (x_L, Q^+) = \omega_L \times d^n (x_L, Q^+) = 0.4556,$$
$$D_M^+ (x_M, Q^+) = \omega_M \times d^n (x_M, Q^+) = 0.3886,$$
$$D_H^+ (x_H, Q^+) = \omega_H \times d^n (x_H, Q^+) = 0.2037,$$
$$D_{VH}^+ (x_{VH}, Q^+) = \omega_{VH} \times d^n (x_{VH}, Q^+) = 0.5638. \quad (17)$$

The normalized Euclidean distance D_i^- from x_i to the SVNPIS can be obtained by Eq. (11), as follows:

$$D_{VL}^- (x_{VL}, Q^-) = \omega_{VL} \times d^n (x_{VL}, Q^-) = 0.2535,$$
$$D_L^- (x_L, Q^-) = \omega_L \times d^n (x_L, Q^-) = 0.2711,$$
$$D_M^- (x_M, Q^-) = \omega_M \times d^n (x_M, Q^-) = 0.8105,$$
$$D_H^- (x_H, Q^-) = \omega_H \times d^n (x_H, Q^-) = 0.4158,$$
$$D_{VH}^- (x_{VH}, Q^-) = \omega_{VH} \times d^n (x_{VH}, Q^-) = 0.2089. \quad (18)$$

(iv) Compute the relative closeness coefficient by Eq. (12). The relative closeness coefficient CC_i is calculated as follows:

$$CC_{VL} = \frac{D_{VL}^- (x_{VL}, Q^-)}{D_{i\max}^- (x_i, Q^-)} - \frac{D_{VL}^+ (x_{VL}, Q^+)}{D_{i\min}^+ (x_i, Q^+)} = -3.4562,$$
$$CC_L = \frac{D_L^- (x_L, Q^-)}{D_{i\max}^- (x_i, Q^-)} - \frac{D_L^+ (x_L, Q^+)}{D_{i\min}^+ (x_i, Q^+)} = -1.9021,$$
$$CC_M = \frac{D_M^- (x_M, Q^-)}{D_{i\max}^- (x_i, Q^-)} - \frac{D_M^+ (x_M, Q^+)}{D_{i\min}^+ (x_i, Q^+)} = -0.9077,$$
$$CC_H = \frac{D_H^- (x_H, Q^-)}{D_{i\max}^- (x_i, Q^-)} - \frac{D_H^+ (x_H, Q^+)}{D_{i\min}^+ (x_i, Q^+)} = -0.4870,$$
$$CC_{VH} = \frac{D_5^- (x_{VH}, Q^-)}{D_{i\max}^- (x_i, Q^-)} - \frac{D_{VH}^+ (x_{VH}, Q^+)}{D_{i\min}^+ (x_i, Q^+)} = -2.5104. \quad (19)$$

where $D_{i\min}^+ (x_i, Q^+) = 0.2037$ and $D_{i\max}^- (x_i, Q^-) = 0.8105$.

According to the descending order of CC_i, the ranking order of fault types is $CC_H > CC_M > CC_L > CC_{VH} > CC_{VL}$. It can be seen that the risk member of component C is " High ".

B. COMPARISON ANALYSIS AND DISCUSSION

In order to further show the effectiveness of the proposed method, a comparative study with other existing method

TABLE 4. The results of the proposed method and existing method.

Linguistics terms	The proposed method (CC_i)	The existing method (the similarity value)
Very-low	-3.4562	0.2122
Low	-1.9021	0.1809
Medium	-0.9077	0.5450
High	-0.4870	0.8768
Very-high	-2.5104	0.7878

is conducted. The proposed method is compared with the method that is introduced by Chutia and Gogoi [59]. With regard to the existing method, the similarity measure is used to determine the final ranking order to obtain the risk of failure. Taking the numerical example of Subsection IV-A as an example, the results of the proposed method and existing method are shown in Table 4.

From the results presented in Table 4, it can be observed clearly that the largest relative closeness coefficient is −0.4870 and the largest similarity value is 0.8768. Therefore, it can be concluded the risk of failure is " High ". By comparison, the result of the proposed method consistent with the result of the existing method, which indicate that the reasonableness and feasibility of the proposed method. The existing method used the similarity measure and it was very difficult to confirm the risk of failure while using measures that have similar characteristic. And the existing method also failed when dealing with uncertainty information in complex environments. However, the proposed method pays more attention to the influence of uncertainty and also introduced the concept of SVNS. The SVNS can handle uncertainty information to improve the reliability of fuzzy risk analysis. Hence, the proposed method provides a robust framework that is a more agile way to handle uncertainty information and avoid information distortion in complex risk environments. In addition, the result of the proposed method is the same as that of the other result with less computational burden.

V. CONCLUSIONS

The determination of risk of failure is key issue in risk assessment of components by semantic model. In the paper, a semantic risk analysis method based on the TOPSIS under SVNS is introduced. Firstly, a five-member linguistic terms set is presented in this paper, and the risk items of each sub-component are evaluated by linguistic terms, which are translated to the generalized trapezoidal fuzzy numbers. Then, the SVNS is determined based on the linguistic values and the linguistic term of a sub-component is properly corrected. On this basis, the SVNPWA operator is used to fuse the generated SVNSs under the same member. Finally, the ranking order can be obtained by TOPSIS to determine risk of failure. This study has dedicated by presenting the SVNS and existing TOPSIS method to deal with fuzzy risk analysis problem. The SVNS can be obtained by the generalized trapezoidal fuzzy numbers, which not only the raw information can be plentifully utilized, but also the uncertainty of risk information is more precise. The SVNS has a powerful ability to represent uncertain and imprecise information, and avoid information loss in complex risk environments. By using the SVNPWA operator to fuse different data under the same member, the accuracy of fuzzy risk analysis is improved. Furthermore, the TOPSIS method is an appropriate tool for determining risk of failure, which is significant in solving fuzzy risk analysis problems. A numerical example and comparing it with the existing method found in the literature are carried out to confirm practical and effective of the proposed method. Further research will mostly concentrate on the following fields. First, the weight of linguistic term of component can be gained by making full use of objective information in the actual work environment. Second, the proposed method can be applied to more practical and complicated cases study to further demonstrate its efficiency and effectiveness.

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LINFENG GOU was born in 1975. He received the B.Sc. degree in flight vehicle propulsion engineering, and the M.Sc. and Ph.D. degrees in Aerospace Propulsion Theory and Engineering from Northwestern Polytechnical University, Xi'an, China, in 1997, 2000, and 2010, respectively, where he is currently an Associate Professor and an Associate Dean with the School of Power and Energy. His research interests include aviation engine control, fault diagnosis, and fault-tolerant control.

MEIJUAN WANG is currently pursuing the master's degree with the School of Electronics and Information, Northwestern Polytechnical University, Xi'an, Shaanxi, China, where she joined Prof. Jiang's guidance team, in 2018. Her current research interests involve evidence theory and information fusion.