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A New Fault Diagnosis Method Based on Attributes Weighted Neutrosophic Set

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ABSTRACT Fault diagnosis is an extensively applied issue to monitor condition and diagnose fault for safe and stable operation of the machine, which started to develop during the industrial revolution and contains various theories and technologies. Due to the growing complexity of contributing factors of a fault and the correlation of fault attributes which are often interrelated, traditional fault diagnosis methods fail to handle with this complex condition. To solve this problem, a new fault diagnosis method based on attributes weighted neutrosophic set is proposed in this paper. In the proposed approach, a attributes weighted model is developed to obtain the weights of attributes by the fault information. For a sample whose fault type is unknown, the neutrosophic set generated from the fault sample data are aggregated via the single valued neutrosophic power weighted averaging (SVNPWA) operator with the obtained attributes weights, then, the fault diagnosis results could be determined by the defuzzification method of fused neutrosophic set. This proposed method have capacity to differentiate the individual impact of attributes and handle the uncertain problems in the process of fault diagnosis. Finally, an illustrative example was provided to demonstrate the reasonableness and effectiveness of the proposed method.

INDEX TERMS Neutrosophic set, fault diagnosis, attributes weighted, defuzzification, SVNPWA operator.

I. INTRODUCTION

Fault diagnosis plays an important role in safe and stable operation of the machines, which was developed from the fault diagnosis of machine equipment by the aerospace industry during the industrial revolution. Fault diagnosis technique applies various theories, such as, reliability theory, information theory, systematology, and has been widely applied to multiple fields, for instance, military [1], [2], economics [3], [4], and medicine [5]–[8]. One of the problems that must be solved when fault diagnosis technology is applied to engineering practice is the robustness of fault diagnosis algorithm. Fault diagnosis system needs to be insensitive to uncertainty of diagnosis environment, which is caused by noise, disturbance and modeling error [9]–[13]. Moreover, there are a great deal of cases that the attributes of fault may be correlative, and which should be considered in the process of fault diagnosis [14]–[16].

With the development of fault diagnosis, immense amount of alternative approaches have been conducted in the literature. According to the professor Frank, who is the international pundit of fault diagnosis fields, all the methods of fault diagnosis can be divided into three kinds: analytical model based approach, signal processing based approach and knowledge-based approach [17]. If a mathematical model of a more accurate controlled process can be established, the method based on the model analysis is the preferred method. The analytical model based approach applies either analytical or knowledge based models, or combinations of both for fault diagnosis, such as, the work of Su and Chen [18]–[20]. If the input and output signals of the controlled process can be obtained and the analytic mathematical model of the controlled object is difficult to be established, the method based on the signal processing can be adopted. The methods based on signal processing also has been applied in multiple fault diagnosis problems, for example, the research of Heydarzadeh *et al.* [21], [22]. When it is difficult to establish a quantitative mathematical model of the controlled object, the knowledge-based method can be

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used. Due to the increased complexity of modern systems, as well as the growing requirements of security and reliability, usually, it is very difficult to obtain the accurate mathematical model of the system. The knowledge-based method does not require accurate mathematical model, such as, convex optimization, classification and statistical learning, probability based methods classifiers and statistical learning methods, especially, evidence theory, and fuzzy set theory have been widely applied in fault diagnosis fields [23], [24]. The fault diagnosis methods suffer from comparatively brief history and immature theory. The requirements of minimizing the uncertainty and dealing with the correlation of fault attributes are still significant research work in this field.

To cope with uncertain information, Smarandache proposed the concept of neutrosophic set from philosophy [25], which are defined by the degree of truth membership, indeterminacy membership and falsity membership took values in the non-standard unit interval, as the extension of the classic set, fuzzy set (FS), intuitionistic fuzzy set (IFS) [26]. However, it is often difficult to apply neutrosophic set in engineering practice, Wang *et al.* introduced the concepts of interval neutrosophic set (INS) and single valued neutrosophic set (SVNS) [27], [28], and Ye proposed the concept of simplified neutrosophic set (SNS) [29], [30], and some theories of them are developed, such as, distance and similarity measures correlation coefficients [31]–[34]. In order to aggregate the neutrosophic set, many neutrosophic aggregation operators have been proposed by researchers [35]. For instance, Peng *et al.* [36] developed some simplified neutrosophic information aggregation operators, such as the simplified neutrosophic weighted averaging (SNWA) operator and the simplified neutrosophic weighted geometric (SNWG) operator. Furthermore, Liu and Luo introduced SVNPWA operator [37]. There have been some fault diagnosis methods based on neutrosophic set, for instance, cotangent similarity based measures and the misfire fault diagnosis method [38]–[40].

In practical fault diagnosis, not always all attributes are of equal importance in diagnosis process. There have been some attributes weighted method [41]–[44], such as, the power average (PA) operator proposed by Yager [45], analytical hierarchy process [45], [46] and so on. Nevertheless, most existing methods do not suit for application under the neutrosophic environment to differentiate the individual impact of attributes.

It is necessary to obtain reasonable weights of attributes for increasing the impact of attributes that show high distinguishability. In addition, there is no definite boundary between the fault state and the normal state, and there are some fuzzy transition states between them. The acquisition of fault information and the reasoning from information to fault result both exist uncertainty. Based on the above discussions, a new fault diagnosis method based on attributes weighted neutrosophic set is proposed in this paper. In the proposed approach, a attributes weighted model is developed for obtaining the weights of attributes by the fault information. The neutrosophic set generated from the fault sample data are aggregated via the SVNPWA operator with the obtained attributes weights, then, the fault diagnosis results could be determined by the defuzzification method of neutrosophic set fused. There are two main traits of this method. Firstly, the developed model could directly determine the weights of fault attributes on the basis of the relative importance of attributes which are transferred by fault information. Afterward, the application of neutrosophic set could handle the uncertainty of fault information and the reasoning process in fault diagnosis.

The remainder of this paper is organized as follows. Section II briefly introduced some basic definition. The developed model is described in Section III. The proposed method for fault diagnosis is listed step by step in Section IV. In Section V, a numerical example is given to illustrate the accuracy and reasonableness of the proposed approach. Some summary remarks are shown in Section VI.

II. PRELIMINARIES

A. NEUTROSOPHIC SET

Neutrosophic set introduced by Smarandache [25] is an extension of the classical FS [47], IFS [48] and IVIFS [49], which is an effective method to solve the problem under uncertain environment. The concept of neutrosophic set is defined as follows [27]:

Definition 1: Let X be a space of points (objects), with a generic element in X denoted by x. A neutrosophic set A in X is characterized by a truth-membership function T_A, an indeterminacy-membership function I_A and a falsity-membership function F_A. $T_A(x)$, $I_A(x)$ and $F_A(x)$ are real standard or non-standard subsets of $]0^-, 1^+[$. That is:

$$\begin{aligned} &T_A : X \mapsto]0^-, 1^+[\\ &I_A : X \mapsto]0^-, 1^+[\\ &F_A : X \mapsto]0^-, 1^+[. \end{aligned} \tag{1}$$

There is no restriction on the sum of $T_A(x)$, $I_A(x)$ and $F_A(x)$, so $0^- \leq supT_A(x) + supI_A(x) + supF_A(x) \leq 3^+$.

B. THE SINGLE-VALUED NEUTROSOPHIC SET

In order to apply neutrosophic set in real scientific and engineering applications, the notion of single valued neutrosophic set (SVNS) [27] is proposed as an instance of neutrosophic set. The definition of SVNS is defined as follows [27]:

Definition 2: Let X be a fixed set, if $\mu_A(x) : X \to [0, 1]$, $\pi_A(x) : X \to [0, 1]$ and $\nu_A(x) : X \to [0, 1]$ satisfied:

$$\begin{aligned} &x \in X \mapsto \mu_A(x) \in [0, 1] \\ &x \in X \mapsto \pi_A(x) \in [0, 1] \\ &x \in X \mapsto \nu_A(x) \in [0, 1] \quad and \\ &0 \leq \mu_A(x) + \pi_A(x) + \nu_A(x) \leq 3, \end{aligned} \tag{2}$$

then an SVNS A in X can be denoted as:

$$A = \{\langle x, \mu_A(x), \pi_A(x), \nu_A(x)\rangle | x \in X\} \tag{3}$$

where $\mu_A(x)$, $\pi_A(x)$ and $\nu_A(x)$ are membership function, indeterminacy-membership and nonmembership function respectively. The numbers $\mu_A(x)$, $\pi_A(x)$ and $\nu_A(x)$ denote, respectively, the degree of membership, the degree of hesitancy and the degree of nonmembership of the element x to A, for all $x \in X$. with the value of $\pi_A(x)$ becomes smaller, the value of x gets more certain. Otherwise, the knowledge about x gets more uncertain.

For a SVNS, an single valued neutrosophic number (SVNN) [50] is denoted by the pair $(\mu_A(x), \pi_A(x), \nu_A(x))$ and each SVNN can be simple denoted as $\alpha = (\mu_\alpha, \pi_\alpha, \nu_\alpha)$, where $\mu_\alpha \in [0, 1]$ and $\mu_\alpha + \pi_\alpha + \nu_\alpha \leq 3$. For an SVNN $\alpha = (\mu_\alpha, \pi_\alpha, \nu_\alpha)$, with the value μ_α gets greater and the value π_α, ν_α gets smaller, the SVNN $\alpha = (\mu_\alpha, \pi_\alpha, \nu_\alpha)$ would be greater .

For any two SVNNs $(\alpha_1 = (\mu_{\alpha 1}, \pi_\alpha 1, \nu_{\alpha 1}), \alpha_2 = (\mu_{\alpha 2}, \pi_\alpha 2, \nu_{\alpha 2}))$, operational relations are defined as following [51]:

$$
\begin{aligned}
&(1)\quad \alpha_1 + \alpha_2 = (\mu_{\alpha_1} + \mu_{\alpha_2} - \mu_{\alpha_1}\mu_{\alpha_2}, \pi_{\alpha_1}\pi_{\alpha_2}, \nu_{\alpha_1}\nu_{\alpha_2}),\\
&(2)\quad \alpha_1 \times \alpha_2 = (\mu_{\alpha_1}\mu_{\alpha_2}, \pi_{\alpha_1} + \pi_{\alpha_2} - \pi_{\alpha_1}\pi_{\alpha_2},\\
&\qquad\qquad \nu_{\alpha_1} + \nu_{\alpha_2} - \nu_{\alpha_1}\nu_{\alpha_2}),\\
&(3)\quad \lambda\alpha_1 = (1 - (1 - \mu_{\alpha_1})^\lambda, \pi_{\alpha_1}^\lambda, \nu_{\alpha_1}^\lambda), \quad \lambda > 0,\\
&(4)\quad \alpha_1^\lambda = (\mu_{\alpha_1}^\lambda, 1-(1 - \pi_{\alpha_1})^\lambda, 1 - (1 - \nu_{\alpha_1})^\lambda), \quad \lambda > 0,\\
&(5)\quad \alpha_1^c = (\mu_{\alpha_1}, 1 - \pi_{\alpha_1}, \nu_{\alpha_1}), \quad \lambda > 0. \qquad (4)
\end{aligned}
$$

Definition 3: Let $\alpha_1 = (\mu_{\alpha_1}, \pi_\alpha 1, \nu_{\alpha_1})$ and $\alpha_2 = (\mu_{\alpha_2}, \pi_\alpha 2, \nu_{\alpha_2})$, the standardized Euclidean distance of two SVNNs is defined as [52]:

$$
D(\alpha_1, \alpha_2) = \sqrt{\frac{(\mu_{\alpha_1} - \mu_{\alpha_2})^2 + (\pi_{\alpha_1} - \pi_{\alpha_2})^2 + (\nu_{\alpha_1} - \nu_{\alpha_2})^2}{3}} \tag{5}
$$

C. THE SVNPWA OPERATOR

Liu proposed some simplified neutrosophic information aggregation operators, such as the SVNPWA operator. It is defined as follows [37]:

Definition 4: Let $A_i = \langle \mu_i, \pi_i, \nu_i \rangle, i = 1, 2, \ldots, n$ be a collection of SVNNs, and $w = (w_1, w_2, \ldots, w_n)^T$ is the weight vector of $A_i (i = 1, 2, \ldots, n)$, with $w_i \in [0, 1]$ and $\sum_{i=1}^{n} w_i = 1$. Then,

$$
\begin{aligned}
&SVNPWA(A_1, A_2, \ldots, A_n)\\
&\quad = \frac{\omega_1 (1+G(A_1)) A_1 \oplus \cdots \oplus \omega_n (1+G(A_n)) A_n}{\sum_{i=1}^{n} \omega_i (1+G(A_i)) A_i}\\
&\quad = \langle 1 - \prod_{i=1}^{n} (1 - \mu_i)^{\xi_i}, \prod_{i=1}^{n} (\pi_i)^{\xi_i}, \prod_{i=1}^{n} (\nu_i)^{\xi_i} \rangle,\\
&\qquad i = 1, 2, \ldots, n.
\end{aligned} \tag{6}
$$

where

$$
\xi_i = \frac{\omega_i (1 + G(A_i))}{\sum_{i=1}^{n} \omega_i (1 + G(A_i))}
$$

$$
G(A_i) = \sum_{\substack{j=1\\ j \neq i}}^{n} Sup(A_i, A_j)
$$

$Sup(A_i, A_j)$ denotes the support for A_i from A_j. Meanwhile, $Sup(A_i, A_j)$ satisfies the following three properties: (1)$Sup(A_i, A_j) \in [0, 1]$; (2)$Sup(A_i, A_j) = Sup(A_j, A_i)$; (3)$Sup(A_i, A_j) \geq Sup(A_k, A_l)$, *if* $| A_i - A_j | < | A_k - A_l |$. It implies that the closer the two sets, the larger the support. And $Sup(A_i, A_j)$ is calculated as follows:

$$
Sup(A_i, A_j) = 1 - d(A_i, A_j)
$$

where

$$
d(A_i, A_j) = \sqrt{\frac{1}{3}\left((\mu_i - \mu_j)^2 + (\pi_i - \pi_j)^2 + (\nu_i - \nu_j)^2\right)}
$$

is the standardized Euclidean distance of two SVNNs.

III. ATTRIBUTES WEIGHTED MODEL

In fault diagnosis problems, the fault types always involves multiple attributes, which may have different relative importance in the diagnosis process. To handle with this problem, the attributes weighted model is proposed in this paper. It is well suited for obtaining the relative weights of attributes to represent the intrinsic information. If the fault data collected in the diagnosis process of all the fault types have little difference regarding certain attribute, it indicates that this attribute plays a less important role in the fault diagnosis problem and should be given a smaller weight. Alternatively, a attribute is relatively more important and should be given a bigger weight in diagnosis process when the fault data shows palpable difference on this attribute. That is, measuring the difference of all fault types' collected data on certain attribute is pivotal for obtaining reasonable weights of attributes.

Normal distribution is one of the most common distribution in nature, the data collected under fault environment are always obey normal distribution. Due to the properties of normal distribution model, the weights of attributes could be defined as follows:

Definition 5: Let $F = F_1, F_2, \ldots, F_m$ be a set of fault types, $C = C_1, C_2, \ldots, C_n$ be a set of fault attributes, $w = (w_1, w_2, \ldots, w_n)^T$ is the weights of attributes:

$$
\omega_i = \frac{1 - sim_i}{\sum_{j=1}^{n} (1 - sim_j)} \tag{7}
$$

And sim_i denotes the overlap degree of all fault types' normal distribution models on attribute C_i, and it is calculated as follows:

$$
\begin{aligned}
sim_i = {} & \frac{O_{12}}{L_1 + L_2 - O_{12}} + \cdots + \frac{O_{1m}}{L_1 + L_m - O_{1m}}\\
& + \frac{O_{23}}{L_2 + L_3 - O_{23}} + \cdots + \frac{O_{2m}}{L_2 + L_m - O_{2m}}\\
& + \cdots + \frac{O_{(m-1)m}}{L_{m-1} + L_m - O_{(m-1)m}}
\end{aligned} \tag{8}
$$

where $L_i = 6 \times \sigma_i$ denotes the relatively effective length of normal distribution model of fault type F_i on certain attribute, σ_i is this normal distribution model's standard deviation, O_{ij} denotes the overlap length between normal distribution models of fault type F_i and fault type F_j on certain attribute.

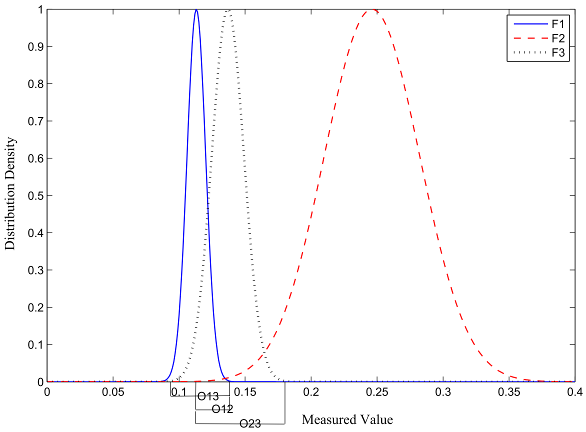

FIGURE 1. **The normal distribution of fault types.**

This definition of attributes' weights model are shown in (Fig. 1). In this figure, the normal distribution figures are generated from three fault types under certain attribute, the overlap intervals between fault types are shown as O_{12}, O_{13} and O_{23}, and the relatively effective length of normal distribution model of certain fault type is defined as $L_i = 6 \times \sigma_i$, σ_i is this normal distribution model's standard deviation. Then the weights of attributes can be calculated via Eq. (7) and Eq. (8).

IV. THE PROPOSED METHOD

In practical fault diagnosis problems, due to the increasing uncertainty of the fault diagnosis process and the complex correlation of attributes, the fault type of unknown fault is not easy to be precisely determined. In this section, a new fault diagnosis method based on attributes weighted neutrosophic set is proposed for diagnosing the fault type of unknown fault sample. Consider an unknown fault sample S with n attributes ($C = \{C_1, C_2, \ldots, C_n\}$), whose data have been collected under each attribute, the proposed method would be used for diagnosing this fault sample S. The flow chart of the proposed method is shown in Fig. 2, and the detailed procedures are elaborated step by step as follows:

(i) Supposed that there are m fault types ($F = \{F_1, F_2, \ldots, F_m\}$) with n attributes ($C = \{C_1, C_2, \ldots, C_n\}$). Collect data of each fault type under each attribute.

(ii) Generate the SVNS for unknown fault sample S based on collected data of fault types. For the data of each fault type under every attributes, generating modified normal distribution model which is obtained by using arithmetic average μ and variance σ^2 of a group of data as the arithmetic average and standard deviation of the normal distribution model, the modified normal distribution is defined as follow:

$$N = e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

denoted as $N(\mu, \sigma^2)$. For the data of the unknown fault sample S, there are a number under each attribute, then this number could generate a line model which is perpendicular to x-axis.

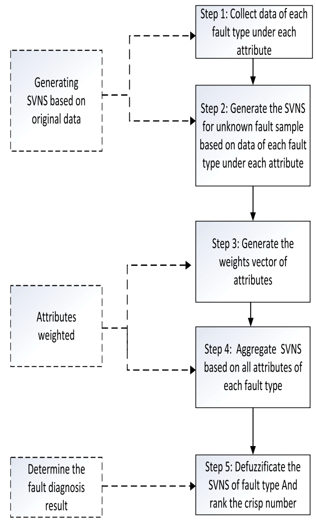

FIGURE 2. **The block diagram of the proposed method.**

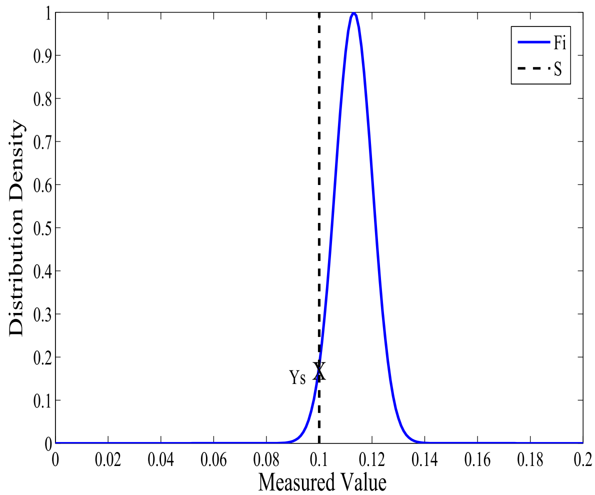

FIGURE 3. **Generation of membership degree.**

The normal distribution function indicates the distribution probability density of the data. The membership degree of SVNS is defined as the value of the vertical coordinate of the intersection point between the line model of S and the normal distribution model of fault type. The curves of two models (Fig. 3) and the definition of membership degree μ are as follows:

$$\mu = y_s, \tag{9}$$

where the y_s represents the value of the vertical coordinate of the intersection point between the unknown fault sample S and fault type F_i.

The nonmembership degree which is correlate with the membership degree is defined as follows:

$$\nu = 1 - \mu, \tag{10}$$

Due to the indeterminacy-membership degree indicates the uncertainty degree of neutrosophic information, it is defined as follows:

$$\pi = \frac{\sigma_i}{\sum_{i=1}^{m} \sigma_i} \tag{11}$$

where the σ_i represents the standard deviation of the data of fault type F_i under certain attribute. Hence, the SVNS generated from Eq. (9,10,11) are as Table 1:

TABLE 1. The generated SVNS for *S* based on fault data data.

Fault Type	Attribute			
	C_1	C_2	$\cdots$	C_n
F_1	$(\mu_{11}, \pi_{11}, \nu_{11})$	$(\mu_{12}, \pi_{12}, \nu_{12})$	$\cdots$	$(\mu_{1n}, \pi_{1n}, \nu_{1n})$
F_2	$(\mu_{21}, \pi_{21}, \nu_{21})$	$(\mu_{22}, \pi_{22}, \nu_{22})$	$\cdots$	$(\mu_{2n}, \pi_{2n}, \nu_{2n})$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
F_m	$(\mu_{m1}, \pi_{m1}, \nu_{m1})$	$(\mu_{m2}, \pi_{m2}, \nu_{m2})$	$\cdots$	$(\mu_{mn}, \pi_{mn}, \nu_{mn})$

(iii) Generate the weights vector of attributes based on fault data via the proposed attributes weighted model in Section III. Then the generated weights vector is as follows:

$$w = [w_1, w_2, \cdots w_n]$$

(iv) Aggregate generated SVNS based on all attributes of each fault type with the weights vector of attributes. The n SVNNs of each fault type would be fused via SVNPWA operator Eq. (6). For inatance:

$$\alpha_1 = SVNPWA(\alpha_{11}, \alpha_{12}, \ldots, \alpha_{1n}) \tag{12}$$

Then, the fused SVNS matrix F is shown as follows:

$$F = \begin{array}{c} F_1 \\ F_2 \\ \vdots \\ F_m \end{array} \begin{bmatrix} (\mu_1, \pi_1, \nu_1) \\ (\mu_2, \pi_2, \nu_2) \\ \vdots \\ (\mu_m, \pi_m, \nu_m) \end{bmatrix}$$

(v) Determine the fault type of the unknown fault sample S. Due to the fuzziness of the unknown fault sample and the fault types, the application of defuzzification method could obtain the result of fault diagnosis, which could reduce the amount of calculation in the process of fault diagnosis. Defuzzy and calculate the crisp number of each SVNN as follows [53]:

$$C_i = \mu_i + (\pi_i)(\frac{\mu_i}{\mu_i + \nu_i}) \tag{13}$$

C_i is the degree of which the information extracted from the data of unknown fault sample support each fault type. As a result, the fault type of the unknown fault sample S would be the fault type whose crisp number C_i is max.

V. ILLUSTRATIVE EXAMPLE AND DISCUSSION

In this section, a case study of a motor rotor is provided to demonstrate the potential applications and validity of the proposed method. As the important part of rotating machinery, motor rotor is the main object of monitoring and diagnosis. This example uses multi-functional flexible rotor test-bed as the experimental equipment. All mechanical equipment in operation will produce certain vibration signals which would change when the fault occurs. When the fault occurs, the frequency and augment of amplitude of different faults are distinct. The vibration energy of three kinds of fault types are mostly concentrated on $1 - 3X$. Therefore, supposed there is an unknown fault sample S_1, and four attributes has been set:

1) C_1: the vibration amplitude when acceleration frequency of the rotor is the basic frequency 1X.
2) C_2: the vibration amplitude when acceleration frequency of the rotor is the frequency 2X.
3) C_3: the vibration amplitude when acceleration frequency of the rotor is the frequency 3X.
4) C_4: average amplitude of vibration displacement in time-domain.

The data in this paper is originated from [54]. The data of S_1 under four attributes has been collected. This group of data of S_1 under four attributes is showed as follows:

$$S_1\ Data = [0.3322 \quad 0.3393 \quad 0.1302 \quad 9.6780]$$

(i) Collect the fault data of each fault type under each attribute. There are three fault types set up on the test-bed:

1. F_1: rotor imbalance.
2. F_2: rotor misalignment.
3. F_3: support base loosening.

For each attribute of each fault type, a group of data were collected. The data in this paper is originated from [54]. For instance, forty number of F_1 under C_1 is showed as follows:

$$\begin{aligned} F_{1C_1}\acute{s}\ partial\ Data = [&0.1663 \quad 0.1590 \quad 0.15680.1485 \quad 0.1723 \\ &0.2006 \quad 0.1903 \quad 0.1908 \quad 0.1986 \quad 0.1843 \\ &0.1785 \quad 0.1610 \quad 0.1579 \quad 0.1511 \quad 0.1532 \\ &0.1647 \quad 0.1628 \quad 0.1646 \quad 0.1634 \quad 0.1642 \\ &0.1648 \quad 0.1640 \quad 0.1674 \quad 0.0661 \quad 0.1659 \\ &0.1650 \quad 0.16330.1632 \quad 0.1604 \quad 0.1542 \\ &0.1555 \quad 0.1562 \quad 0.15400.1564 \quad 0.1557 \\ &0.1542 \quad 0.1546 \quad 0.1571 \quad 0.1537 \quad 0.1536] \end{aligned}$$

(ii) Generate the SVNS for unknown fault sample S_1 based on fault data. Each group of data of each fault type under each feature is used for establishing the modified normal distribution model. The generated normal distributions of fault types and the line model of unknown fault sample S_1 are listed in Table 2:

TABLE 2. Multiple distribution of fault types and unknown fault sample.

Fault type	Attribute			
	C_1	C_2	C_3	C_4
F_1	N(0.1619,0.0101)	N(0.1488,0.0173)	N(0.1131,0.0071)	N(4.3035,0.3204)
F_2	N(0.1821,0.0136)	N(0.3320,0.0106)	N(0.2461,0.0362)	N(4.7533,0.4653)
F_3	N(0.3301,0.0075)	N(0.3459,0.0142)	N(0.1370,0.0122)	N(9.7948,0.0888)
S_1	x=0.3322	x=0.3393	x=0.1302	x=9.6780

TABLE 3. The generated SVNS for S_1 based on fault data of every fault types under every features.

Fault Type	Attribute			
	C_1	C_2	C_3	C_4
F_1	(0.0000,0.3232,1.0000)	(0.0000,0.4109,1.0000)	(0.0543,0.1276,0.9457)	(0.0000,0.3664,1.0000)
F_2	(0.0000,0.4370,1.0000)	(0.7862,0.2514,0.2138)	(0.0058,0.6517,0.9942)	(0.0000,0.5321,1.0000)
F_3	(0.9622,0.2398,0.0378)	(0.8981,0.3377,0.1019)	(0.8587,0.2207,0.1413)	(0.4209,0.1015,0.5791)

Then calculate the SVNS by the Eq. (9)(10)(11). For instance, the distribution of S_{1C_1} *Data* is $x = 0.3322$, the distribution of F_{1C_1} *Data* is $N(0.1619, 0.0101)$, the SVNN generated from the two distributions is (0.0000, 0.3232, 1.0000). The generated SVNS are listed in Table 3.

(iii) Generate the weights vector of attributes based on fault data via the proposed attributes weighted model in Section III. The figures of modified normal distribution models of three fault types under four attributes are as Fig. 4:
Then the generated weights vector is as follows:

$$w = [0.2913, 0.2075, 0.2903, 0.2108]$$

(iv) Aggregate generated SVNS based on all attributes of each fault type. Fusing the SVNNs based on the four attributes of each fault type by SVNPWA operator Eq. (6) with the wights vector w. Take the SVNNs based on fault type F_1 as an example, it could be fused as follows:

$$\begin{aligned}\alpha_1 &= SVNPWA(\alpha_{11}, \alpha_{12}, \alpha_{13}, \alpha_{14})\\ &= SVNPWA((0.0000, 0.3232, 1.0000),\\ &\quad (0.0000, 0.4109, 1.0000),\\ &\quad (0.0543, 0.1276, 0.9457),\\ &\quad (0.0000, 0.3664, 1.0000))\\ &= (0.0158, 0.2675, 0.9842)\end{aligned}$$

The others are shown in Table 4.

(v) Determine the fault type of the unknown fault sample S_1. Finally, using the defuzzification method Eq. (13) to deal with the SVNNs fault diagnosis matrix which is shown in Table 4. The crisp numbers and their ranks of three fault types are shown in Table 5.

TABLE 4. The result of fusing the four attributes' SVNNs based on each fault type.

Fault Type	SVNS
F_1	(0.0158,0.2675,0.9842)
F_2	(0.2382,0.4672,0.7618)
F_3	(0.8829,0.2131,0.1171)

TABLE 5. The rank of the crisp number of three fault types.

Fault type	crisp number	rank
F_1	0.020050	3
F_2	0.349535	2
F_3	1.071004	1

According to the above rank result, the fault type of S_1 diagnosed by the proposed method is F_3, which is identical with the actual fault type. The reasonableness of the proposed method could be demonstrate via this diagnosis results, and the advantage of the proposed method would be shown as follows.

Moreover, the proposed method is used for verifying 120 unknown fault samples, and the accuracy of diagnosis results is 98.33%. And equal weights in the aggregating process is also applied for diagnosing the same 120 unknown fault samples, the accuracy of diagnosis results is 93.33%. The diagnosis results are shown as Table 6.

According the comparison results in Table 6, it can be seen that the attributes weighted is significant in fault diagnosis problems. It is widely admitted that the attributes of fault may have different relative importance in the diagnosis process. The proposed method defines a attributes weighted model

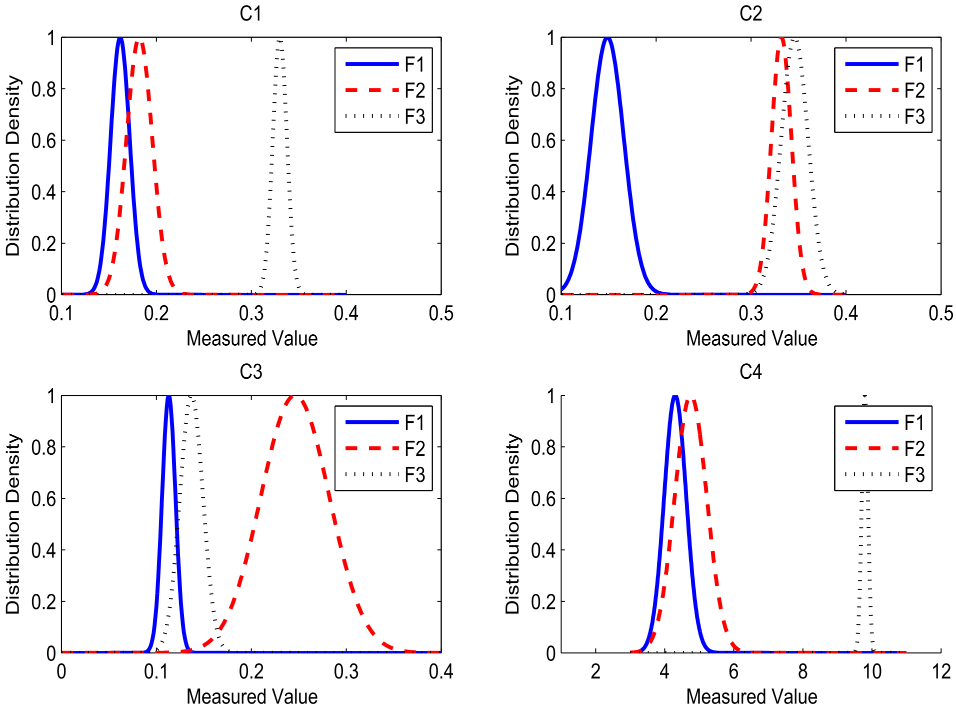

FIGURE 4. Generation of weights of attributes.

TABLE 6. Diagnosis results of applying the proposed method and equal weights.

Unknown Fault	The proposed Method		Equal Weights	
	times of right	times of error	times of right	times of error
F_1	38	2	38	2
F_2	40	0	40	0
F_3	40	0	34	6

based on the similarity of distribution of fault data to derive attributes' weights, which avoids the subjective randomness of selecting the attributes weights; while some approach just assumes that all the attributes have equal weights and some approach gives the wights of attributes directly in the diagnosis process, which may produce the unreasonable final diagnosis results. Based on the above comparison analysis, it can be concluded that the combination of the attributes weighted model, neutrosophic set and SVNPWA operator could handle with the different importance of attributes and uncertainty in the fault diagnosis problems, which could obtain accurate diagnosis results.

VI. CONCLUSION

Fault diagnosis is an widely applied issue to monitor condition and diagnose fault for safety and reliability. However, the relative importance of attributes and some uncertain factors failed to be considered in the fault diagnosis process. Confronted with this problem, a new fault diagnosis method based on attributes weighted neutrosophic set is proposed in this paper. In the proposed approach, a attributes weighted model is developed for obtaining the weights of attributes with the fault information. The focus of this method include three points: firstly, the different importance of attributes in diagnosis process is obtained in this proposed attributes weighted model with the completely unknown weight information, which is convenient and reasonable for obtaining attributes' weights; afterward, the uncertainty of fault types and unknown fault sample both are considered in the application of neutrosophic set; finally, the SVNPWA operator could be used for aggregating the SVNS, which considers uncertainty of fault information indicated with the neutrosophic set. The application prospect of the proposed method in solving the fault diagnosis problem is optimistic. Further work will focus on the application of neutrosophic set with the proposed attributes weighted model, and the subjective weights of attributes would be considered in the fault diagnosis problem.

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