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# Expression and Analysis of Scale Effect and Anisotropy of Joint Roughness Coefficient Values Using Confidence Neutrosophic Number Cubic Values

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**Abstract**: The JRC data collected from a rock mass joint surface difficultly obtain enough large-scale JRC sample data, but small-scale JRC sample data, which usually contain indeterminate and incomplete information due to the limitation of the measurement environment, measurement technology, and other factors. In this case, the existing representation and analysis methods of the JRC sample data almost all lack the measures of confidence levels in the sample data analysis. In this paper, we propose the concept and expression method of confidence neutrosophic number cubic values (CNNCVs), and then establish CNNCVs of joint roughness coefficient (JRC) (JRC-CNNCVs) from the limited/small-scale JRC sample data subject to the normal distribution and confidence level of the JRC sample data to analyze the scale effect and anisotropy of JRC values. In the analysis process, the JRC-CNNCVs are first conversed from the JRC sample data (multi-valued sets) in view of their distribution characteristics and confidence level. Next, JRC-CNNCVs are applied to analyze the scale effect and anisotropy of the JRC values by an actual case, and then the effectiveness and rationality of the proposed expression and analysis method using JRC-CNNCVs are proved by the actual case in a JRC multi-valued environment. From a perspective of probabilistic estimation, the established expression and analysis method makes the JRC expression and analysis more reasonable and reliable under the condition of small-scale sample data.

**Keywords:** confidence neutrosophic number; confidence neutrosophic number cubic value; joint roughness coefficient; scale effect; anisotropy

#### **1. Introduction**

Joint roughness coefficient (JRC) was first proposed by Barton [1] and estimated through experience. Then, JRC is a key index that affects the shear strength of the rock joint. To make the JRC value more reasonable and accurate, researchers have proposed many calculation and expression methods of the JRC value, such as statistical parameter methods [2, 3], straight edge methods [4–7], fractal dimension methods [8–11], etc. However, the indeterminate and incomplete information contained in the JRC values is not considered in the above studies. Due to the irregularity of the rock mass joint surface, the JRC values at different positions on the same joint are different, which also means that the JRC values imply some uncertainty. Numerous studies have shown that the JRC values reflect their scale effect [12–15] and decrease with increasing sample scale. Another obvious characteristic of the JRC values is anisotropy [16–19], that is, the JRC values in different measurement directions of the same rock mass joint is different. Both of these characteristics reflect incomplete and indeterminate information contained in the JRC values. Furthermore, some studies [20, 21] have shown that sampling bias is also an important factor causing the indeterminacy of JRC values.

As an important branch of neutrosophic theory, a neutrosophic number (NN) was first proposed by Smarandache [22–24] from the perspective of the symbol. Then, Ye [25–27] gave the calculation rules of NNs from the perspective of the numerical value and generalized their application in practical problems. Subsequently, related theories of NN have been applied to the decision making/evaluation of investment projects, manufacturing schemes, software testing, goal programming, air quality, etc. [28–33]. NN can generally be expressed as  $E(I) = v + \eta I$ , where *v* is the determinate part and *ηI* is the indeterminate part, the indeterminacy  $I \in [I^L, I^U]$ , and  $v, \eta \in R$  (all real numbers). According to an indeterminate range of  $I \in [I^{\perp}, I^{\perp}]$ , NN can represent all values in an interval. Therefore, it is very suitable for the expression of the JRC value because NN can express incomplete and indeterminate information flexibly and conveniently. Yong et al. [34] applied NN to the expression of the JRC value and utilized the NN function to analyze the anisotropy and scale effect of the JRC values. Although this research effectively considers the uncertainty in the JRC values, this method requires the use of a fitting function, where may loss some useful information in the fitting process. To avoid this defect, some scholars combined the theory of neutrosophic statistics with NN to express the JRC values by JRC-NNs [35–37]. Furthermore, Chen et al. [38] combined neutrosophic probability with NN and proposed neutrosophic interval probability (NIP) and neutrosophic interval statistical number (NISN) to express JRC values. Although this method makes the JRC-NN/interval value confident to a certain degree, this method still lacks some probabilistic estimation since the confidence level/interval of the neutrosophic probabilities (*PT*, *PI*, *PF*) is not considered in NIP. It is difficult to ensure the probabilistic credibility of the JRC values within the NIP obtained from the limited JRC sample data. Then, Zhang and Ye [39] presented (fuzzy) confidence neutrosophic number cubic sets (CNNCSs) in a fuzzy multi-valued setting and used them for group decision-making problems with fuzzy multi-valued sets. Motivated by the notion of the fuzzy CNNCS, this paper introduces a confidence NN cubic value (CNNCV) in light of the probability distribution and confidence level of multi-valued sets. Then, considering the probability distribution and confidence level of the JRC values in the actual environment of small-scale JRC sample data, we convert the JRC multi-valued sets obtained from the rock mass in Changshan County (Zhejiang Province, China) into JRC-CNNCVs as the mixed representation form of the JRC confidence intervals and the JRC average values. The proposed expression method of JRC-CNNCVs can ensure that the JRC values fall within confidence neutrosophic numbers (CNNs) (confidence intervals with some confidence level of  $(1-\alpha)$ %) from a probabilistic point of view and reveal the magnitude of the JRC mean. Finally, the scale effect and anisotropy of the JRC values are analyzed by JRC-CNNCVs to verify the validity and rationality of the proposed expression and analysis method in the actual environment of the limited/small-scale JRC sample data. Under the condition of small-scale JRC sample data, the expression and analysis method proposed in this study reflects the obvious advantage, as it is more suitable for engineering applications.

The rest of this paper is organized as follows. Section 2 gives the definition of CNNCV in view of the fuzzy CNNCS. Section 3 converts the actual measured JRC multi-valued sets into JRC-CNNCVs in terms of the normal distribution and confidence level of the JRC values, and then analyzes the scale effect and anisotropy of the JRC values by JRC-CNNCVs. Finally, conclusions and further research are given in Section 4.

#### **2. CNNCVs**

In this section, we give the definition of CNNCV in terms of the normal distribution of a multivalued set and the confidence level of  $(1-\alpha)$ % for a level  $\alpha$  as an extension of the fuzzy CNNCS.

First, we introduce the notions of NN [22–24], NN probability [40], and CNN [39, 40]. The NN *E*(*I*) = *v* + *ηI* consists of two parts, including the determinate part *ω* and the indeterminate part *ηI* subject to the indeterminacy  $I \in [I^L, I^U]$  and  $v, \eta \in R$ . Obviously, NN (changeable interval number for

 $I \in [I^L, I^U]$  can conveniently express both the determinate information and the indeterminate information contained in the indeterminate situation by  $E(I) = [v + \eta I^L, v + \eta I^U]$ . Especially when considering  $E(I)$  as the value of a random variable *t* in  $[v + \eta I, v + \eta I^{\text{U}}]$  with the distribution function *p*(*t*) (e.g., normal distribution function), the definition of NN probability is introduced as follows [40]:

$$
P(t) = p(v + \eta I^{L} \le t \le v + \eta I^{U}) = \int_{v + \eta I^{L}}^{v + \eta I^{U}} p(t) dt.
$$
 (1)

The larger the NN probability for the variable *t*, the larger the range of indeterminacy *I*, that is, the larger the indeterminate interval.

Assuming that there is a multi-valued set  $X = \{x_1, x_2, \ldots, x_n\}$  and  $x_i (i = 1, 2, \ldots, n)$  in *X* obeys the normal distribution, then the average value *v* and the standard deviation *k* of the data in *X* are given as follows:

$$
v = -\frac{1}{n} \sum_{i=1}^{n} x_i \tag{2}
$$

$$
k = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - v)^2}
$$
 (3)

Thus, the multi-valued set *X* with a confidence level of  $(1-\alpha)$ % can be converted into the CNNCV  $Ex(I_{\alpha})$  by the following equation:

$$
E_X(I_\alpha) = \left\langle [E^L(I_\alpha), E^U(I_\alpha)], \nu \right\rangle = \left\langle \left[ \nu + \eta I^L, \nu + \eta I^U \right], \nu \right\rangle = \left\langle \left[ \nu - \frac{k}{\sqrt{n}} t_{\alpha/2}, \nu + \frac{k}{\sqrt{n}} t_{\alpha/2} \right], \nu \right\rangle, \quad (4)
$$

where the indeterminate range of  $I_\alpha$  is  $[I^L, I^U] = [-t_{\alpha/2}, t_{\alpha/2}]$  and  $t_{\alpha/2}$  is the critical value that is adopted from [39, 40] in view of confidence levels of  $(1-\alpha)$ % (commonly take  $t_{\alpha/2}$  = 1.645, 1.96, 2.576 for the confidence levels of 90%, 95% and 99% [40]).

**Example 1.** There is a multi-valued set *B* = {6.32, 1.56, 2.39, 18.35, 10.32, 2.33, 5.77, 3.98, 8.82, 16.32, 9.35, 15.98, 5.58, 11.90, 10.06, 9.33, 5.52, 12.48, 4.46, 10.28} with the normal distribution. Then, the conversing process from the multi-valued set *B* to the CNNCV *E<sup>B</sup>* is shown below.

First, the mean and standard deviation of the multi-valued set *B* can be calculated by Eqs. (2) and (3):

(i) 
$$
v_B = \frac{1}{n} \sum_{i=1}^{n} b_i = \frac{1}{20} \sum_{i=1}^{20} b_i = 8.56
$$
;  
(ii)  $k_B = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (b_i - v_B)^2} = 4.82$ 

Using Eq. (4) with the most common confidence level of 95% and the critical value  $t_{\alpha/2} = 1.96$  [40], the CNNCV *E<sup>B</sup>* corresponding to *B* can be obtained below:  $\mathbf{v}$ 

$$
E_B = \left\langle \left[ v_B + \eta_B I^L, v_B + \eta_B I^U \right], v_B \right\rangle = \left\langle \left[ v_B - \frac{k_B}{\sqrt{n}} t_{\alpha/2}, v_b + \frac{k_B}{\sqrt{n}} t_{\alpha/2} \right], v_B \right\rangle
$$
  
=  $\left\langle \left[ 8.56 - 1.96 \times 4.82 / \sqrt{20}, 8.56 + 1.96 \times 4.82 / \sqrt{20} \right], 8.56 \right\rangle = \left\langle [6.45, 10.67], 8.56 \right\rangle$ ,

.

where the indeterminate range of *I* is  $[I^L, I^U] = [-t_{\alpha/2}, t_{\alpha/2}] = [-1.96, 1.96]$ .

From this example, we get the CNNCV  $E_B = \langle 6.45, 10.67 \rangle$ , 8.56>, which is composed of the CNN/confidence interval [6.45, 10.67] and the mean 8.56 of *B* at the confidence level of 95%. Then, we can see that converting the multi-valued set into CNNCV can ensure that 95% probability of the data in *B* will fall within the CNN/confidence interval [6.45, 10.67], and then 5% probability of the data in *B* will be outside the CNN/confidence interval [6.45, 10.67], while the mean 8.56 of *B* reveals the magnitude of the data. Therefore, this conversion approach reflects the advantages of rationality and credibility from the perspective of probabilistic estimation under the condition of small-scale sample data.

#### **3. JRC-CNNCV expression and analysis approach for JRC values**

The shear strength of the rock joint surface is recognized as a key parameter in the stability evaluation of engineering rock mass, then JRC is the most important factor affecting the shear strength of the rock mass joint. In practical engineering, the JRC values usually contain a lot of indeterminate and incomplete information, and the measurement of the JRC values is also often limited by the rock joint surface. Therefore, CNNCVs are very suitable for expressing the limited/small-scale JRC sample data.

In this section, we first express the JRC values collected from the rock mass in Changshan County (Zhejiang Province, China) [38] by CNNCVs to give JRC-CNNCVs (including the JRC confidence intervals and the average values). To do so, we introduce the measured data of 240 JRC sample data under 10 sample sizes in 24 measurement directions, and the number of sample data in each multivalued set is 35. During the measurement process, the measurement directions are divided into 24 directions from 0° to 345° at 15° intervals, and the sample scales are divided into 10 sizes from 10 cm to 100 cm at 10 cm intervals [38]. Then using Eqs. (2) and (3), we calculated the mean *v* and the standard deviation *k* of each JRC multi-valued set, which are shown in Table 1.

Many existing studies [41–44] have noted that the distribution of JRC values approximates the normal distribution or left-biased normal distribution after statistical analysis of the JRC values of large-scale sample data. Therefore, in this study, we regard the distribution of the JRC values related to the limited sample data as the normal distribution. In view of the mean and standard deviation of the JRC values, the JRC values (multi-valued sets) are converted into the JRC-CNNCVs at the confidence level of 95% by Eqs. (2)-(4).

Taking the JRC values with the measurement direction of  $0^{\circ}$  and the sample size of 10 cm as an example, the JRC values are converted into JRC-CNNCV by the following calculation process.

First, it can be seen from Table 1 that the average value *v* of the JRC values corresponding to the 10 cm sample size in the 0° measurement direction is 10.5861 and the standard deviation *k* is 2.3026 subject to the 35sample data.

Then using Eq. (4) with the confidence level of 95% and  $I_\alpha = [I^L, I^U] = [-1.96, 1.96]$ , we can get the following JRC-CNNCV:

$$
E_{JRC} = \left\langle \left[E^{L}(I_{\alpha}), E^{U}(I_{\alpha})\right], \nu \right\rangle = \left\langle \left[\nu + \eta I^{L}, \nu + \eta I^{U}\right], \nu \right\rangle = \left\langle \left[\nu - \frac{k}{\sqrt{n}} t_{\alpha/2}, \nu + \frac{k}{\sqrt{n}} t_{\alpha/2} \right], \nu \right\rangle
$$

 $=\langle\boxed{10.5861-1.96\times2.3026\,/\,\sqrt{35},10.5861-1.96\times2.3026\,/\,\sqrt{35}}\rceil, 10.5861\rangle = \langle\boxed{9.8233,11.3490},10.5861\rangle.$ 

By the similar calculation way, JRC-CNNCVs of *E<sub>JRC</sub>* corresponding to the JRC values in other measurement directions and sample sizes are shown in Table 2.

Direction $(°)$	Size (cm)	$\boldsymbol{v}$	k	Direction $(°)$	Size (cm)	$\boldsymbol{v}$	k
$\mathbf{0}$	10	10.5861	2.3026	180	10	9.8462	2.1651
	20	9.6833	1.7374		20	9.9489	1.8742
	30	9.3136	1.5113		30	8.7877	1.7512
	40	9.0054	1.7304		40	8.6400	1.6939
	50	8.8621	1.6416		50	8.3278	1.6074
	60	8.8322	1.6281		60	8.1673	1.6464
	70	8.6922	1.6222		70	7.9951	1.5076
	80	8.6070	1.5109		80	7.9080	1.3551
	90	8.5757	1.3621		90	7.8390	1.2001
	100	8.4684	1.2872		100	7.8343	1.0682
15	10	10.7113	2.2212	195	10	9.7585	2.2466

**Table 1.** The mean *v* and the standard deviation *k* of JRC values obtained from 24 different directions under 10 different sample sizes





40	8.9070	1.6206	40	8.5143	1.2073
50	8.6527	1.5085	50	7.8935	1.1648
60	8.6762	1.6154	60	7.8888	1.0518
70	8.4030	1.3793	70	7.7577	1.0386
80	8.1164	1.2253	80	7.4773	0.9410
90	7.9124	1.1049	90	7.1833	0.8261
100	7.7224	0.9357	100	7.0093	0.7396

**Table 2.** JRC-CNNCVs of *EJRC* in 24 different directions under 10 different sample sizes







As shown in Table 2, JRC-CNNCV reflects the mixed information of the confidence interval and the mean of the JRC values at the confidence level of 95%, which is different from the traditional expression methods of JRC-NNs. Furthermore, JRC-CNNCV reveals that 95% probability of the JRC data will fall within CNNs corresponding the confidence level of 95% and the mean magnitude of the JRC data. In this case, the confidence level can effectively guarantee the rationality and credibility of *EJRC* from a probabilistic point of view. From a perspective of probabilistic estimation, the JRC-CNNCVs of *EJRC* in Table 2 can contain 95% probability of the actual JRC values, but cannot contain 5% probability of them based on the probability estimation of the JRC values corresponding to different measurement directions and sample sizes.

To analyze the scale effect and anisotropy of the JRC values by the expression method of JRC-CNNCVs, we give Figures 1-3 and their analysis in detail.

Figure 1 shows the *E<sub>IRC</sub>* values at different sizes in the measurement directions of 0°, 90°, 180°, and 270° from Table 2 and the average values of the corresponding JRC values in Table 1. As shown in Figure 1, the upper and lower bounds of JRC-CNNs and the JRC average values in the same measurement direction show a decreasing trend with the increase of the sample size, which is in line with the scale effect of the JRC values. At the same time, we can find that the standard deviation of the JRC values corresponding to each measurement direction generally shows a decreasing trend with the increase of the sample size. In Figure 2, taking the measurement direction of 15° as an example, the confidence intervals in *EJRC* shrink with the increase of the sample size in the same direction, and then the JRC-CNNs and the JRC average values decrease with the increase of the

sample size. This case also means that the uncertainty about the JRC values is diminishing with the increase of the sample size. In addition, we select the confidence intervals and the average values in *E*<sub>*IRC*</sub> in the measurement directions from 0° to 345° under the sample sizes of 10 cm, 40 cm, 70 cm, and 100 cm to draw polar plots in Figure 3. As shown in Figure 3, the interval values of [*EL*, *EU*] and the average values of *v* in different measurement directions under the same size are different, which reflect the anisotropy of the JRC values. Meanwhile, with increasing sample size, the upper and lower bounds of CNNs in different measurement directions under the same size are also close to each other, and the interval ranges of CNNs and the average values in  $E_{JK}$  are decreasing, which indicates the scale effect of the anisotropy of the JRC values. The above conclusions show that the JRC values expressed by JRC-CNNCVs can also reflect indeterminate and incomplete information contained in the anisotropy of the JRC values. Therefore, it is obvious that the expression and analysis method using JRC-CNNCVs proposed in this study can effectively reveal the scale effect and anisotropy of the JRC values, then the proposed method is obviously superior to the existing methods regarding their rationality and credibility in the application scenarios of small-scale sample data.



**Figure 1.** (**a**) *EJRC* (JRC-CNNCVs) corresponding to JRC values at different sizes in the 0° direction; (**b**) *EJRC* (JRC-CNNCVs) corresponding to the JRC values at different sizes in the 90° direction; (**c**) *EJRC* (JRC-CNNCVs) corresponding to the JRC values at different sizes in the 180° direction; (**d**) *EJRC* (JRC-CNNCVs) corresponding to the JRC values at different sizes in the 270° direction.



**Figure 2.** *EJRC* (JRC-CNNCVs) corresponding to the JRC values of different sizes in the 15° direction



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**Figure 3.** (**a**) *EJRC* (JRC-CNNCVs) corresponding to the JRC values of different measurement directions under 10 cm sample size; (b)  $E_{\text{JRC}}$  (JRC-CNNCVs) corresponding to the JRC values of different measurement directions under 40 cm sample size; (**c**) *EJRC* (JRC-CNNCVs) corresponding to the JRC values of different measurement directions under 70 cm sample size; (**d**) *EJRC* (JRC-CNNCVs) corresponding to the JRC values of different measurement directions under 100 cm sample size

#### **4. Conclusions**

Since it is difficult to usually obtain enough large-scale JRC sample data from rock mass joint surfaces due to the limitation of the measurement environment, measurement technology, and other factors, there exists some indeterminate and incomplete information in small-scale JRC sample data. In this case, the existing representation and analysis methods of JRC sample data almost all lack the measures of confidence levels in sample data analysis. Then, the JRC-CNNCV expression obtained from the limited/small-scale JRC sample data can effectively solve the above problems and ensure that the JRC values can fall within CNN with a certain confidence level. Unlike classical statistics which takes the JRC values as crisp values, JRC-CNNCV transformed from the JRC values is composed of the confidence interval and the average value, so the uncertainty and incompleteness contained in the JRC values can be fully reflected by the probabilistic estimation within a confidence interval. As the extension and improvement of the existing JRC-NN expression methods for JRC values, the JRC-CNNCV expression method can effectively ensure the reliability of the small-scale sample data so as to lessen the loss of useful information and simplify the analysis process. In addition, through the expression and analysis method using JRC-CNNCVs for the JRC values of an actual case, this study also revealed the scale effect and anisotropy of the JRC values so as to further verify the effectiveness and convenience of the proposed expression and analysis method. It is clear that the proposed expression and analysis method can further enhance the credibility of the analysis results on the JRC characteristics (the scale effect and anisotropy of the JRC values) from a probabilistic point of view. In the future, CNNCVs combined with other analysis methods will present more in-depth analysis of the scale effect and anisotropy of the JRC values, and the CNNCV expression and analysis method will be further extended to engineering or experiment data processing.

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