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A Novel Risk Matrix Approach Based on Cloud Model for Risk Assessment Under Uncertainty

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ABSTRACT The fuzziness and randomness are significant epistemic uncertainty within the qualitative categorization of the two critical factors, the frequency and severity, which are not fully considered in the traditional risk matrix. This paper mainly proposes a cloud risk matrix method for the risk assessment of process safety considering the epistemic uncertainty in expert elicitation. The cloud model is employed to provide a mathematical expression for the fuzziness and randomness in the linguistic variables by its two numerical characteristics entropy En and hyperentropy He. An adjusted Mamdani inference algorithm is constructed for the determination of an integrated risk cloud given the value of input variables. And the centroid method is improved to be adapted to the calculation of risk index from the enormous cloud droplets in the integrated risk cloud. A case study of risk assessment for distillation column unit is performed to illustrate the process of cloud risk matrix in detail, and the validity and rationality are verified by contrast to the results from the fuzzy risk matrix. Results indicate the proposed method can handle the randomness of qualitative concepts, which is more suitable to the practical condition. Moreover, the effect of the hyperentropy He on the randomness of risk index is also investigated and discussed for the reference to parameter selection. The proposed cloud risk matrix can provide an effective risk inference tool in a wide range of engineering fields.

INDEX TERMS Risk matrix, cloud model, risk assessment, Mamdani inference algorithm, process safety.

I. INTRODUCTION

Predictive risk analysis and evaluation for industrial process safety have obtained more attention because of the increasing complexity of production systems and the reduction of people's tolerance to undesired incidents. The failure of a component in a complex system can easily cause a domino effect, bringing a series of bad performances of other parts or even catastrophic events. Hazard materials with flammability, toxicity, or pollution escaping from the processing system may result in a serious threat to the safety of human life, property, and environment. The main purpose of risk assessment for a process system is to identify the potential failure causes, determine the risk degree, find the critical failure paths and allocate the limited resources rationally to reduce the risk of accident as much as possible. The prediction of hazardous events is mainly concerning the frequency of occurrence and the severity of consequence [1]. Even though other factors may also be regarded as important judgment indicators, such as detectivity and maintainability [2], [3].

Risk assessment involves a wide range of quantitative and qualitative techniques [4], such as the fault tree analysis (FTA) [5], the Bayesian network (BN) [6], [7], the Petri net (PN) [8], the failure mode and effect analysis (FMEA) [9], the layer of protection analysis (LOPA) [10] and the risk assessment matrix (RAM) [11]. The risk matrix approach was developed to conduct the risk assessment of life cycle of purchase project by US Airforce in 1995 [12]. Over the past decades, the risk matrix approach has become one of the most popular risk assessment methods utilized in a variety of engineering fields [13]–[16]. This method has provided a simple tool to rank and prioritize the risk of events [17] and helped the decision-makers to determine the acceptability of the risks.

The risk matrix can be carried out qualitatively, quantitatively or semi-quantitatively [18], which depends on how

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the risk factors would be expressed, what kind of mapping relationship would be adopted, and the form of the assessment results. It is constructed on the basis of the combination of the frequency of occurrence and the severity of consequence. As for a certain incident to be evaluated, the domain of frequency and severity must be defined according to common sense or engineering practice and divided into several levels. The categorization of frequency and severity can be defined both in numerical terms and in linguistic terms. Accordingly, the mapping relationship from frequency and severity to the risk index can be constructed by mathematical functions or knowledge-based inference rules. Ni *et al*. [19] summarized the binary functions and some arithmetic extensions on the risk matrix and established a risk-matrix-style assessment framework. When it comes to linguistic variables, the knowledge of domain experts can be used to establish the mapping relationship in terms of inference rules, by which the risk level can be judged as for any combination of the existing variable level of frequency and severity. This manner can provide greater flexibility than the mathematical functions and has been adopted by many researchers and standards [20], [21].

However, some limitations must be taken seriously in the application of linguistic variables and expert subjective judgments. The sharp boundary of different levels is not according with the real condition which would lead to wrong conclusions. Input values dropping in both sides of the boundary of levels, although similar to each other, would produce diverse risk values, which is not consistent with common sense. That means the range of the qualitative concept is not certain. As for the same linguistic term, different experts could have various understanding, or the same person may have distinct sense perception in different circumstances. Therefore, randomness and fuzziness [22] are two kinds of critical uncertainties in human cognition that should be given full consideration in quantitative mathematical description and operation. The fuzziness of linguistic variables in the risk matrix has received some attention. Many researchers have provided some theories to deal with this kind of uncertainty. Fuzzy set theory has been extensively used to describe the fuzziness based on the concept of membership. Markowski and Mannan [23] employed fuzzy logic into the risk matrix to overcome the uncertainties and imprecision connected with the traditional risk matrix. On the other hand, the randomness of concepts means that any concept is not an isolated fact but is related to the external world in various ways [24]. However, few studies have focused on the randomness in the risk matrix method base on linguistic inference rules, even though the randomness of linguistic terms has been more and more considered in expert assessment or group decision-making based on human cognition [25], [26].

The cloud model, a new cognitive model proposed by Li *et al*. [27], has provided an effective tool for representing the randomness and fuzziness in human cognition. It has the great ability to convert between qualitative concepts and quantitative values [28]. Probability theory and fuzzy set theory are the theoretical basis of the cloud model to reflect the uncertainty in concepts. The normal distribution is one of the most popular probability distributions to depicting random phenomena, and the normal membership function has been extensively utilized to measure the fuzziness of an element belonging to a qualitative concept [29]. Advantages of the two mathematical tools are integrated by the cloud model which can reflect the membership degree of an element to a fuzzy concept in the manner of random membership. Wu *et al*. [30] proposed an extended Vlsekri-terijumska Optimizacija I Kompromisno Resenje (VIKOR) method under linguistic information to evaluate the uncertainty of potential supplier quantitatively and scientifically. Yan *et al*. proposed a cloud model layer of protection analysis (CM-LOPA) [31] and a cloud model-preliminary hazard analysis (CM-PHA) [32] to process the expert judgments and present the quantified risk of gas leakage in a biomass gasification station. Liu *et al*. [33] provided a combined FMEA method with the Technique for Order Preference by Similarity to ideal solution method (TOPSIS) and cloud models to solve complex decision-making problems. Therefore, the cloud model is adopted to modified the risk matrix approach by dealing with the fuzziness and randomness in the linguistic variables.

And the fuzzy inference system (IFS) would be employed to comprehensively aggregate various inference rules, represented by linguistic variables, in a specific scenario to produce the assessment result. The Mamdani fuzzy inference system [34] is one of the most popular inference algorithms, which has been extensively utilized in various inference processes [35], [36]. Monjezi *et al.* [37] have described and illustrated the detailed process of Mamdani inference including two inference rules. Given the input values of all antecedent variables, the output data can be computed by the min operator for every inference rule, and the membership function will be discounted by this output value. Then, the max operator is adopted to perform the aggregation process of all discounted membership functions from each rule. The antecedent variables and conclusion variables are all represented by fuzzy sets and the exact value of membership degree can be obtained as for any input data in the domain. However, the cloud model will produce a random output value of membership degree as for any input data. And the membership function in the universe of discourse is no longer a smooth curve so that the aggregation process cannot be performed according to the original manner, as well as the defuzzification process subsequently. Therefore, the Mamdani fuzzy inference algorithm and the defuzzification process must be adjusted to be suitable for the cloud model.

The purpose of this paper is to develop a novel cloud risk matrix approach based on the cloud model to deal with the randomness and fuzziness in the qualitative concepts. To the best of the authors' knowledge, this is the first study in the risk matrix approach that uses the cloud model to represent the linguistic variables in the categorization of risk matrix variables, and achieve the Mamdani inference and defuzzification process in terms of random membership degree.

The remaining part of this article is organized as follows: A brief review of basic theories and concepts of the risk matrix, fuzzy risk matrix, and cloud model is presented in Section 2. Section 3 presents the proposed cloud risk matrix method for risk assessment in detail. A case study of the risk assessment for a distillation column unit through the proposed method is implemented in Section 4. The results obtained from the proposed approach are compared with that from the traditional fuzzy risk matrix in Section 5, meanwhile, discussions about the randomness of the risk index and the key influence factor are presented. Lastly, Section 6 includes some concluding remarks.

II. PRELIMINARIES

This section will review some basic concepts in correlation to the proposed cloud risk matrix, including the risk matrix, fuzzy risk matrix, and cloud model.

A. RISK MATRIX APPROACH

The risk of an accident scenario is defined as the combination of the likelihood of occurrence and the severity of consequences in the risk matrix [38]. The frequency index and severity index are usually the only two input variables to determine the output risk index.

Frequency, severity, and risk index are classified as different levels according to industry practice or actual engineering requires, and assigned the corresponding score. Different algorithms[19] appeared to obtain the risk index based on different arithmetic operators, such as multiplication shown in Eq.(1).

$$R = F \times S \tag{1}$$

The risk index R is defined as the product of frequency F and severity index S, which means a positive relationship with the latter two variables.

On the other hand, the risk level could be deduced by knowledge-based rules, which are usually presented by the following classical logic implication.

If the frequency is level "f", and severity is level "s", then the risk is level "r".

The manner of inference rules can provide more flexible definitions of the risk level in different regions in the risk matrix. Domain experts or decision-makers have relatively high authority to give a set of rules of which the number depends on the categorization and scaling of the two input variables. Different kinds of risk matrices can be constructed based on the given rules. Markowski and Mannan [23] described three different risk matrixes including "standard", "easy", and "hard" matrix, and discussed the safety and economy.

B. FUZZY RISK MATRIX

The fuzzy logic system has been introduced into the risk matrix to handle the fuzziness in linguistic evaluation. The main procedures of the risk matrix approach consist of the fuzzification, the inference process, and the defuzzification procedure [23].

In the fuzzification process, the crisp input values are transferred into fuzzy sets based on the definitions of the set of qualitative variable levels. Each input value will correspond to multiple linguistic terms with exact membership values.

During the inference procedure, different fuzzy sets of frequency and severity will be combined based on each knowledge-based rule and a comprehensive fuzzy set is obtained to measure the overall risk level. The Mamdani fuzzy inference algorithm [39] contributes an effective method, as shown in Eq.(2).

$$\mu_R(r) = \max_k \left(\min \left(\mu_F^k(f), \mu_S^k(s) \right) \right) \tag{2}$$

where the f, s represent the frequency index and severity index respectively, k is the number of rules, $\mu_F^k(f)$ and $\mu_S^k(s)$ are the membership of value f and s to the level F and S under the kth rule. And the $\mu_R(r)$ is the aggregated membership of any r in the universe of discourse.

Defuzzification is the process of converting the comprehensive risk fuzzy set into a crisp risk index. In the fuzzy risk matrix, the comprehensive risk fuzzy set is usually shown as an irregular geometric figure when plotted. The centroid method is a commonly utilized algorithm to perform the defuzzification process, in which the abscissa of the gravity center of the geometric figure is taken as the corresponding exact number of the comprehensive fuzzy number. The formula of the centroid method is shown as Eq.(3).

$$r = \frac{\int \mu_R(r) r dr}{\int \mu_R(r) dr} \tag{3}$$

The fuzzy risk matrix has settled the problem of fuzziness among different qualitative linguistic variables. However, the membership function for each linguistic term is defined as a deterministic function, which may be not perfectly suitable to the real state. It's difficult to judge exactly how much membership degree a certain value belongs to a specific qualitative concept.

C. CLOUD MODEL

The cloud model can synthetically describe the randomness and fuzziness of qualitative concepts, and be able to implement uncertain transformations between a qualitative concept and its quantitative instantiations[40]. The definition of the cloud model is as follow:

Definition [27]: As for any qualitative concept T in a universe of discourse U, assume that $x \in U$ is a random instantiation of T, and the certain degree of x belonging to T is determined as $y \in [0, 1]$, which satisfies the following formula:

$$y = e^{-\frac{(x-Ex)^2}{2En'^2}},$$

where

$$x \sim N\left(Ex, En'^2\right), \quad En' \sim N\left(En, He^2\right).$$

The distribution of x in U is defined as a normal cloud, and any binary ordered pair (x, y) can be called a cloud drop. A normal cloud can be expressed as $\tilde{y} = (Ex, En, He)$ where the three critical characters are expectation Ex, entropy En, and hyperentropy He. The expectation Ex is the center of the cloud droplets, which reflects the average value of the concept described. The entropy En defines the effective range of the universe of discourse U, which embodies the ambiguity. The hyperentropy He could illustrate the thickness of the dot cloud, which means the dispersion degree of the qualitative concept.

Forward cloud generator can produce a lot of cloud drops in a figure to illustrate the qualitative concept based on given Ex, En, He and the number of drops n. The detailed procedures can be summarized as follow:

(1) Generate n random numbers En_i' that comply with normal distribution $N(En, He^2)$;
(2) Generate n normally distributed random numbers x_i based on the expectation Ex and each variance En_i';
(3) Obtain n random membership values μ_i that satisfy Eq.(4).

$$\mu_i = \exp\left(-\frac{(x_i - Ex)^2}{2En_i'^2}\right) \tag{4}$$

(4) The n ordered pairs (x_i, μ_i) make up the cloud.

If the specific value a is given, it is required to generate the random membership values based on a certain cloud $\tilde{y} = (Ex, En, He)$ where the precondition cloud generator [41] can be used.

III. MODEL DEVELOPMENT

In this section, the proposed cloud risk matrix for risk assessment is described in detail. Domain experts' knowledge and experience can be solid down in terms of variables classification definitions and inference rules. The main contribution of the proposed methodology includes: The cloud model is introduced into the risk matrix to deal with the fuzziness and randomness in qualitative concepts that portray the variable classifications. An adjusted Mamdani inference algorithm is constructed to perform the inference process. Meanwhile, an improved centroid method is constructed to convert the discrete cloud drops into a crisp risk index.

The proposed cloud risk matrix will be implemented mainly in three critical procedures, as shown in Fig. 1. Firstly, the classifications of risk matrix variables are determined based on the industrial customs, decision-makers' preferences, and experts' knowledge and experience. Fuzzification and randomization of these classifications are implemented in the use of cloud models. The characteristic numbers of the cloud models to measure the variables for frequency levels, severity levels, and risk levels will be defined. Therefore, the given crisp frequency index f_0 and severity index s_0 can be converted into random cloud droplets that reflect the membership degree to different levels. Secondly, the changed Mamdani inference algorithm will handle these random cloud

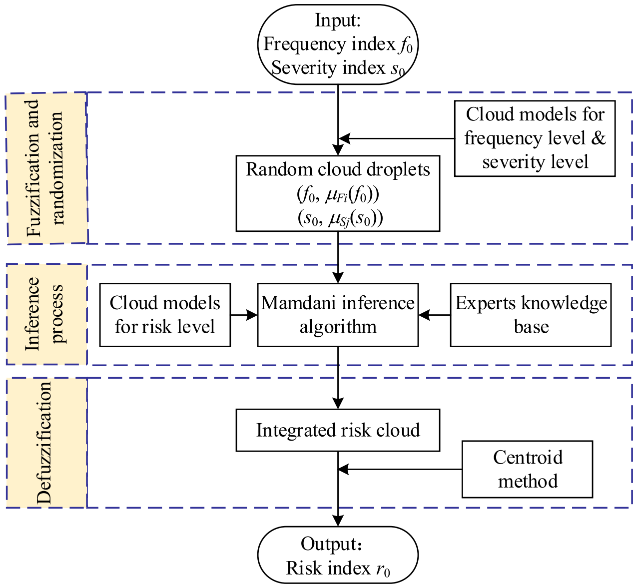

FIGURE 1. Frame for cloud risk matrix.

droplets, utilizing the experts' knowledge in terms of inference rules, to produce an integrated risk cloud that represents the overall risk level. Thirdly, the defuzzification process is conducted to transform the integrated risk cloud into a crisp risk index that provides a quantitative assessment result by the improved centroid method suitable for cloud models.

A. FUZZIFICATION AND RANDOMIZATION

Frequency, severity, and risk index are the only three variables in the risk matrix, of which the universe of discourse should be divided into several levels and numerical intervals according to the industrial customs or decision-makers' suggestions. To deal with the epistemic uncertainty in the qualitative concepts for each level, a set of normal cloud models are defined to provide mathematical expressions for these linguistic terms. In this study, the categorization and scaling of each variable from Markowski and Mannan [23] are employed as an example for further calculation and validation of the proposed cloud risk matrix.

Characteristic numbers of the cloud models for these variables are defined as in TABLE 1, in which the fuzziness and randomness in different level concepts can be described. Each cloud is expressed in form of $Cloud(a, b, c)$ with a as the expectation, b as the entropy, and c as the hyperentropy. Meanwhile, the Gaussian fuzzy numbers for these variables used in the fuzzy risk matrix are also listed in TABLE 1, where the $N(a, b)$ means a normal fuzzy number with the a as the expectation and b as the standard deviation. As can be seen, the expectation and entropy of the cloud model are the same as the expectation and the standard deviation of the corresponding fuzzy number respectively, which can ensure the similar shape of the figure produced. The hyperentropy is defined as $He = 0.05$ for all clouds here, of which the rationality will be given further discussion later. Fig. 2 presents

TABLE 1. Categorization and cloud models for variables in a risk matrix.

Linguistic variables	Linguistic terms	Description range	Gaussian fuzzy number	Cloud model
Frequency (*F*)	Very High -G	$1<F<10^{-2}$	*N*(-7, 0.42) (right)	*Cloud*(-7, 0.42, 0.05) (right)
	High-F	$10^{-1}<F<10^{-3}$	*N*(-6, 0.42)	*Cloud*(-6, 0.42, 0.05)
	Moderate-E	$10^{-2}<F<10^{-4}$	*N*(-5, 0.42)	*Cloud*(-5, 0.42, 0.05)
	Low-D	$10^{-3}<F<10^{-5}$	*N*(-4, 0.42)	*Cloud*(-4, 0.42, 0.05)
	Very Low-C	$10^{-4}<F<10^{-6}$	*N*(-3, 0.42)	*Cloud*(-3, 0.42, 0.05)
	Unlikely-B	$10^{-5}<F<10^{-7}$	*N*(-2, 0.42)	*Cloud*(-2, 0.42, 0.05)
	Remote-A	$F<10^{-6}$	*N*(-1, 0.42) (left)	*Cloud*(-1, 0.42, 0.05) (left)
Severity (*C*)	Negligible-A	[1, 2]	*N*(1, 0.42) (right)	*Cloud*(1, 0.42, 0.05) (right)
	Low-B	[2, 3]	*N*(2, 0.42)	*Cloud*(2, 0.42, 0.05)
	Moderate-C	[3, 4]	*N*(3, 0.42)	*Cloud*(3, 0.42, 0.05)
	High-D	[4, 5]	*N*(4, 0.42)	*Cloud*(4, 0.42, 0.05)
	Catastrophic-E	[5, 6]	*N*(5, 0.42) (left)	*Cloud*(5, 0.42, 0.05) (left)
Risk (*R*)	A：Acceptable	[0, 2]	*N*(1, 0.42)	*Cloud*(1, 0.42, 0.05)
	TA：Tolerable-Acceptable	[1, 3]	*N*(2, 0.42)	*Cloud*(2, 0.42, 0.05)
	TNA：Tolerable-Unacceptable	[2, 4]	*N*(3, 0.42)	*Cloud*(3, 0.42, 0.05)
	NA：Unacceptable	[3, 5]	*N*(4, 0.42)	*Cloud*(4, 0.42, 0.05)

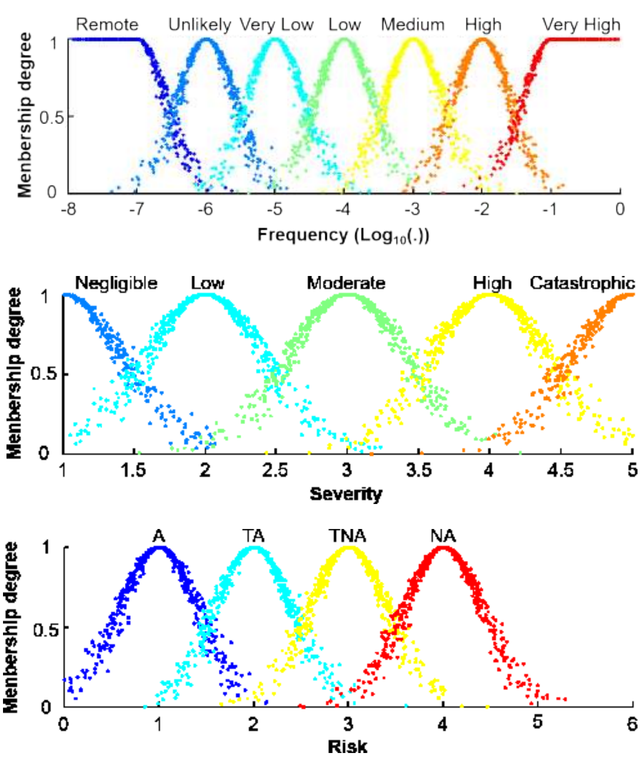

FIGURE 2. Cloud models for different categorizations of variables.

the different categorizations and clouds for each value used in the cloud risk matrix with different colors.

B. INFERENCE PROCESS

The inference process is implemented by a set of inference rules based on experts' knowledge and experience. Inference rules usually appear in the form of ''IF-Then'' rules. Frequency and severity are the two input variables of the risk matrix to be converted into the output variable risk index so that the former valuables are the antecedents and the latter one is the conclusion. These rules constitute the basis of the inference process and can be used for the judgment of risk level in a traditional risk matrix. While in the cloud risk matrix, the concepts in the antecedents and conclusion of each rule will be expressed by cloud models and an inference algorithm helps to handle the discrete cloud drop data.

The Mamdani inference algorithm is a popular fuzzy inference method that has been utilized in multiple inference scenarios based on knowledge-based rules [40]. The classical Mamdani algorithm is suitable for the processing of fuzzy numbers with definite membership value. Given any values f, s in the domain of discourse, the unique membership values $\mu_F^k(f)$ and $\mu_S^k(s)$ will be determined under the certain rule k. The membership value of output valuable can be obtained by comparing the ones of the input valuables, shown as $\mu_R^k(r) = \min\left(\mu_F^k(f), \mu_S^k(s)\right)$. Integrating the results from all the rules, a comprehensive fuzzy membership function representing the synthetic reasoning results is obtained $\mu_R(r)$. As for any value in the domain of risk, there is only one membership value $\mu_R(r)$. The mapping relationship between any risk index and its membership degree constitutes a continuous function. Therefore, the defuzzification risk index can be further obtained by the function integral operation.

However, in the proposed cloud risk matrix, the membership degree for any exact input value in the domain is not a definite number but a random result, therefore, the classical Mamdani inference algorithm is not perfectly suitable for the inference process of cloud variables. An adjusted Mamdani inference algorithm is constructed to perform the inference process. The main procedures of Mamdani inference based on the cloud model including the following steps.

(1) Calculate the random membership values for each frequency level and severity level according to the given

frequency index and severity index. And the vector of random membership degree is obtained as $\mu_F = [\mu_{F1}(f_0), \mu_{F2}(f_0), \ldots, \mu_{F7}(f_0)]$ and $\mu_S = \mu_{S2}(s_0), \ldots, \mu_{S5}(s_0)]$. Each random membership value is computed by the precondition cloud generator. For example, as for the fourth frequency level "Low", the corresponding cloud model is presented as *Cloud*(−4, 0.42, 0.05), the random membership value can be calculated as $\mu_{F4}(f_0)$, as shown in Eq.(5).

$$\mu_{F4}(f_0) = \exp\left[-\frac{(f_0 - Ex)^2}{2E_{nn}^2}\right] \tag{5}$$

where $Ex = -4, En = 0.42, He = 0.05, E_{nn}$ represents a random number that obeys the normal distribution $N\left(En, He^2\right)$.

(2) Determine the effectiveness of valuables. If the membership degree of the input index is too low under a certain variable level, it indicates that there is a big gap between the current input variable index and the qualitative concept described by the variable level, and the contribution to the integrated cloud model can be ignored. Therefore, the variable level is defined as an invalid variable level under the current input variable index, which can be ignored in the subsequent comprehensive calculation, to reduce the calculation time and improve the computational efficiency.

Set the threshold value of invalid variable grade $err = 0.1$. If the random membership $\mu_{Fi}(f_0)$, $\mu_{Sj}(s_0)$ of frequency grade F_i, or consequence grade S_j is greater than err, the frequency grade and its random membership value will be saved. If it is less than err, the grade and its random membership will be discarded. Finally, there are m effective frequency levels $EF_m = (F_m, \mu_{Fm}(f_0))$ and n consequence levels $ES_n = (S_n, \mu_{Sn}(s_0))$ that would be obtained.

(3) Inference of the membership degree of each risk level. According to the reasoning rules based on expert knowledge, the risk level R_k corresponding to each effective frequency level Fm and effective consequence level Sn is determined one by one, and the random membership degree of risk level k under the rule is calculated by $\mu_{Rk}^{mn}(r) = min(\mu_{Fm}^{k}(f_0), \mu_{Sn}^{k}(s_0))$. Then the random membership values of each risk level k are compared comprehensively, and the maximum value is selected as the maximum membership value of risk level k, namely $\mu_{Rk}(r) = \underset{mn}{max}(\mu_{Rk}^{mn}(r))$.

(4) Obtain a comprehensive risk cloud. The comprehensive risk cloud reflects the comprehensive distribution result of risk membership degree under all reasoning rules for the given frequency index and consequence index. In the domain of risk index, N values r_i are evenly or randomly selected. The random membership degree under risk level k is obtained using the method shown in Eq.(5) and compared with the maximum membership degree of risk level k obtained in step (3). The smaller value is selected as the random membership degree under risk level k. After the calculation of all risk levels k, the maximum value is selected as the comprehensive membership degree of r_i, as shown in Eq.(6).

$$\mu_R(r_i) = \max_k \mu_R^k(r_i) \tag{6}$$

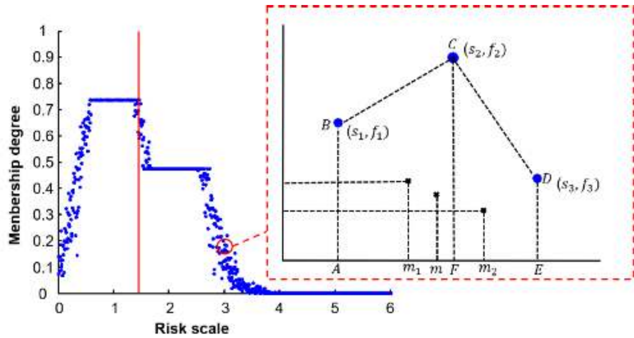

FIGURE 3. Comprehensive risk cloud model and the local cloud drops.

Drawing the above N cloud drops $(r_i, \mu_R(r_i))$ $(i = 1, 2, \ldots N)$ in the coordinate system, we can get the comprehensive risk cloud model under the given frequency index f_0 and severity index s_0, as shown in Fig. 3.

C. DEFUZZIFICATION

Defuzzification is the process of transforming the comprehensive risk cloud into a deterministic risk index to measure the risk level of the evaluation object quantitatively. The comprehensive risk cloud takes the risk index as the abscissa and the random membership degree of each point as the ordinate to form a group of discrete cloud droplets with stable tendency, which reflects the fuzziness and randomness of the comprehensive evaluation results.

The centroid method is widely used in the defuzzification process of synthetic fuzzy numbers. The core idea of the centroid method is to take the position of the geometric centroid of synthetic fuzzy numbers in the coordinate system as the determined value after defuzzification, which is used to express the certainty index of the synthetic concept. However, the classical centroid method is suitable for the case with a certain fuzzy membership function. The membership image within the scale of risk index is a continuous curve, and the position of the geometric centroid can be directly calculated by an integral operation.

To handle the discrete cloud drops in the integrated risk cloud, an improved defuzzification method is constructed as an extension of the classical centroid method. A variety of right angle trapezoids are constructed according to the discrete random cloud drops in the comprehensive risk cloud in turn. The geometric centroid of the random point cloud graph is obtained by superposition calculation, and the comprehensive risk cloud is transformed into the comprehensive risk index.

The defuzzification process of the integrated risk cloud can be seen in Fig. 3. More specifically, the N random cloud droplets (s_i, f_i) contained in the integrated risk cloud are arranged in ascending order according to the abscissa s_i to form N-1 trapezoids. The abscissa of the geometric centroid of each trapezoid is shown in Eq.(7). According to the relative positions of the top and bottom in the trapezoid, the calculation process of the abscissa of the geometric centroid

TABLE 2. Input variable values and the results from the cloud risk matrix and fuzzy risk matrix.

Accident scenarios				RAS(R)1	RAS(L)2	RAS(R)3	RAS(L)4
Input	Frequency index			1.44E-7	6.27E-6	1.44E-7	6.27E-6
	Severity index			4.35	4.08	4.55	4.28
Output	Risk index	Fuzzy risk matrix	Easy	1.18	1.84	1.23	1.83
			Standard	1.35	2.01	1.56	2.25
			Hard	2.18	2.97	2.56	3.01
		Cloud risk matrix	Easy	1.2042	1.9954	1.2588	1.7296
			Standard	1.3371	2.0577	1.5966	2.1930
			Hard	2.3223	2.9248	2.3196	2.9034

is slightly different. For the trapezoid ABCF and the trapezoid EDCF in Fig. 3, the abscissa of the geometric centroid can be computed by Eq.(8) and Eq.(9) respectively.

$$m_i = \begin{cases} s_{i+1} - \dfrac{(2f_i + f_{i+1})\,(s_{i+1} - s_i)}{3\,(f_i + f_{i+1})}, & f_i \le f_{i+1} \\ s_i + \dfrac{(2f_{i+1} + f_i)\,(s_{i+1} - s_i)}{3\,(f_i + f_{i+1})}, & f_i > f_{i+1} \end{cases} \tag{7}$$

$$m_1 = s_2 - \frac{(2f_1 + f_2) \times (s_2 - s_1)}{3\,(f_1 + f_2)} \tag{8}$$

$$m_2 = s_2 + \frac{(2f_3 + f_2) \times (s_3 - s_2)}{3\,(f_2 + f_3)} \tag{9}$$

Repeat the above calculation process, calculate the geometric centroid of each trapezoid, and summarize them, as shown in Eq.(10). And the comprehensive risk index m corresponding to the comprehensive risk cloud can be obtained. The geometric centroid of the overall risk cloud is illustrated by the red line in Fig. 3.

$$m = \frac{\sum_{i=1}^{n-1} (s_{i+1} - s_i) \times (f_{i+1} + f_i) \times m_i}{\sum_{i=1}^{n-1} (s_{i+1} - s_i) \times (f_{i+1} + f_i)} \tag{10}$$

IV. CASE STUDY

To verify the feasibility and effectiveness of the proposed method, the risk assessment case of the distillation tower unit carried out by Markowski and Mannan [23] and other researchers are selected as an example. The cloud risk matrix method is performed and the results are compared with that from the traditional fuzzy risk matrix. Four accident scenarios (RAS) due to loss of cooling are selected for distillation column unit failure, which will lead to rupture of column (R) and leak from relieving valve (L). The input frequency index and severity index of the four accident scenarios are shown in TABLE 2.

The process of cloud risk matrix is illustrated in detail using the accident scenario RAS(R)1 as an example, where the input frequency index is $f_0 = \log_{10}(1.44\text{E-7}) = -6.84$ and the severity index is $s_0 = 4.35$.

Firstly, based on the categorization and cloud models defined in Fig. 2, the vector of random membership values for frequency and severity level is obtained as $\mu_F = [0.9452, 0.1520, 0, 0, 0, 0, 0]$ and $\mu_S = [0, 0, 0.0298, 0.7248, 0.2802]$.

Secondly, the $err = 0.1$ is defined as the threshold value of the invalid variable grade. The effective frequency levels and the random membership values include $EF_1 =$ (“Remote”,0.9452) and $EF_2 =$ (“Unlikely”, 0.1520). Meanwhile, the effective severity levels and the random membership values are $ES_1 =$ (“High”, 0.7248) and $ES_2 =$ (“Catastrophic”, 0.2802). The other variable grades are defined as invalid variable grades because their random membership value is lower than the judgment threshold err, and do not participate in the subsequent calculation process.

Thirdly, the risk level and membership degree are inferred based on the inference rules. The “standard” risk matrix rules are adopted. Based on the effective levels of frequency and severity, the required inference rules are listed as follow:

$$\begin{aligned} &\textit{if } F = \text{"Remote"},\ \textit{and } S = \text{"High"},\ \textit{then } R = \text{"A"}; \\ &\textit{if } F = \text{"Remote"},\ \textit{and } S = \text{"Catastrophic"},\ \textit{then } R = \text{"TA"}; \\ &\textit{if } F = \text{"Unlikely"},\ \textit{and } S = \text{"High"},\ \textit{then } R = \text{"TA"}; \\ &\textit{if } F = \text{"Unlikely"},\ \textit{and } S = \text{"Catastrophic"},\ \textit{then } R = \text{"TA"}; \end{aligned}$$

The membership value can be obtained based on each inference rule by the following *min* operation.

$$\begin{aligned} \mu_{R1}^{11}(r) &= min(\mu_{EF1}^{1}(f_0), \mu_{ES1}^{1}(s_0)) = 0.7248; \\ \mu_{R2}^{12}(r) &= min(\mu_{EF1}^{2}(f_0), \mu_{ES2}^{2}(s_0)) = 0.2802; \\ \mu_{R2}^{21}(r) &= min(\mu_{EF2}^{2}(f_0), \mu_{ES1}^{2}(s_0)) = 0.1520; \\ \mu_{R2}^{22}(r) &= min(\mu_{EF2}^{2}(f_0), \mu_{ES2}^{2}(s_0)) = 0.1520; \end{aligned}$$

As can be seen, the risk levels involved in the above inference rules include R_1 “A” and R_2 “TA”, and the maximum membership value for each level are $\mu_{R1}(r) = 0.7248$ and $\mu_{R2}(r) = 0.2802$ respectively.

The cloud-based Mamdani inference process is illustrated in Fig. 4. The rows of the figures show a graphical representation of the required inference rules. The first column is the effective frequency levels, the second column is the effective consequence levels, and the third column is the risk levels obtained. Each subgraph is labeled with the variable level cloud model and random membership. The blue part below the red dotted line is the effective cloud droplets, and the red part is the invalid ones, which are higher than the current random membership value.

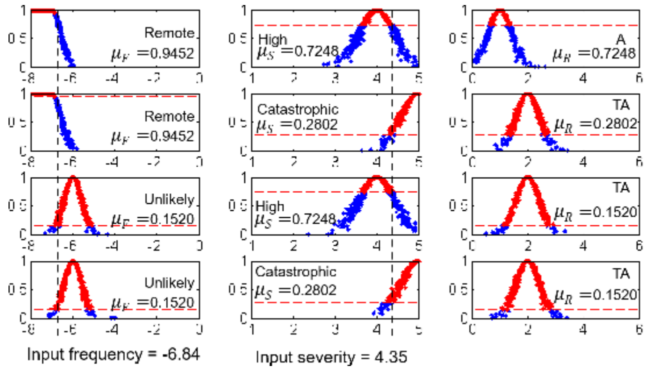

FIGURE 4. Inference process based on cloud models.

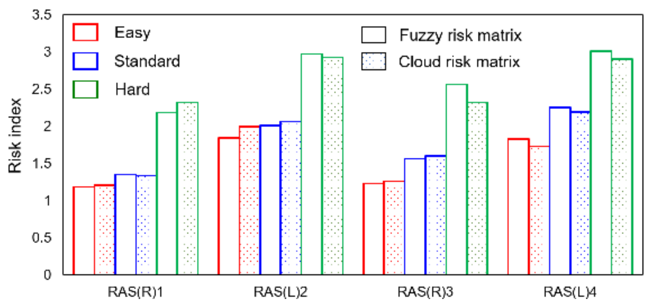

FIGURE 5. Comparison of the results.

Fourthly, integrate the risk level R_k and its maximum membership degree $\mu_{Rk}(r)$ to obtain the comprehensive risk cloud. A number of $N = 1000$ values of r_i are selected evenly in the domain of risk index [0,6]. The random membership values $\mu_{R1}(r_i)$ and $\mu_{R2}(r_i)$ are calculated under the risk level R_1 and R_2. Compare the $\mu_{R1}(r_i)$ with $\mu_{R1}(r) = 0.7248$ and take the smaller one as the random membership value $\mu_R^1(r_i)$ of risk R_1, so as to $\mu_R^2(r_i)$ of risk R_2. Then, compare $\mu_R^1(r_i)$ with $\mu_R^2(r_i)$, and take the bigger one as the final comprehensive membership degree $\mu_R(r_i)$. A number of $N = 1000$ ordered pairs $(r_i, \mu_R(r_i))$ are produced and the comprehensive risk cloud can be obtained by plotting these droplets in a figure, as shown in Fig. 3.

Eventually, perform the improved centroid method and obtain the final risk index. Through the process of sorting, constructing right-angle trapezoid, calculating centroid and integral operation, these cloud droplets are mapped into a crisp risk index $r = 1.3771$, as shown in the red line in Fig. 3.

V. RESULTS AND DISCUSSIONS

A. RESULTS AND COMPARISON

According to the above calculation process, the comprehensive risk indexes of four accident scenarios in the case can be calculated respectively based on the reasoning rules of different types, which can be used as a quantitative index to evaluate the risk degree of accident scenarios. The results are shown in TABLE 2 and compared in Fig. 5.

The red area, the blue area and the green area in Fig. 5 are the results obtained according to the type of "simple", "standard", and "difficult" inference rules respectively. The unfilled area is the result of the fuzzy risk matrix, and the filled area represents that of the cloud risk matrix.

As can be seen, the comprehensive risk index given by the cloud risk matrix is slightly different from that obtained from the fuzzy risk matrix under the same type of inference rules. Through numerical comparison, it can be concluded that the law of size is not consistent, and there is no phenomenon that the results of certain methods are uniformly larger or smaller. These differences are caused by the randomness of the cloud model. Given the same input values, the results of multiple calculations have randomness to a certain extent. Fig. 5 only shows the comprehensive risk index of a particular calculation, therefore, it appears that the results are larger or smaller than those of the fuzzy risk matrix. But the relative gaps between results are small and the risk indexes are close in different initial conditions, which indicates the effectiveness of the proposed model.

By analyzing the results of different types of inference rules, it can be seen that the ranking of risk index results is consistent, namely "Hard" > "Standard" > "Simple". This phenomenon is caused by the definition of inference rules. In the "if A, then B" type of rules, for the same antecedent A, the "Hard type" rule defines the derived result B as a higher risk level, and the risk index value is relatively larger. Therefore, the consistency of the sorting results can show the rationality of the proposed cloud risk matrix.

B. THREE-DIMENSIONAL RISK SURFACE

Three-dimensional risk surface can vividly display the mapping relationship between frequency index, consequence index, and risk index. It is a graphical description of expert knowledge inference rules. Therefore, the inference rules are the core content of the three-dimensional risk surface, which directly affects the shape and distribution.

A three-dimensional risk surface can be constructed using a cloud risk matrix by considering all the combinations of frequency index and severity index in the domain. In this paper, 20 values are evenly obtained respectively from the frequency index domain [−8,0] and the consequence index domain [1,5]. These risk indexes under any combination can be calculated based on the "Easy", "Standard", and "Hard" inference rules, and are drawn in a 3-dimensional coordinate system, as shown in Fig. 6.

These risk surfaces illustrate the overall distribution characteristics of the risk level. As for the ‘‘Easy’’ type matrix, the lower risk level occupies a larger area while the higher risk level dose in the ‘‘Hard’’ type matrix. As can be seen, the transition of risk regions is not smooth because the randomness of the risk index brings the possibility of great difference among the evaluation results of close coordinate points.

C. SOURCE OF THE RESULTS RANDOMNESS

To further illustrate the randomness introduced in the calculation process, the accident scenario RAS(R) 1 is taken as an example to carry out multiple calculations. The results of comprehensive risk clouds and risk indexes are compared and

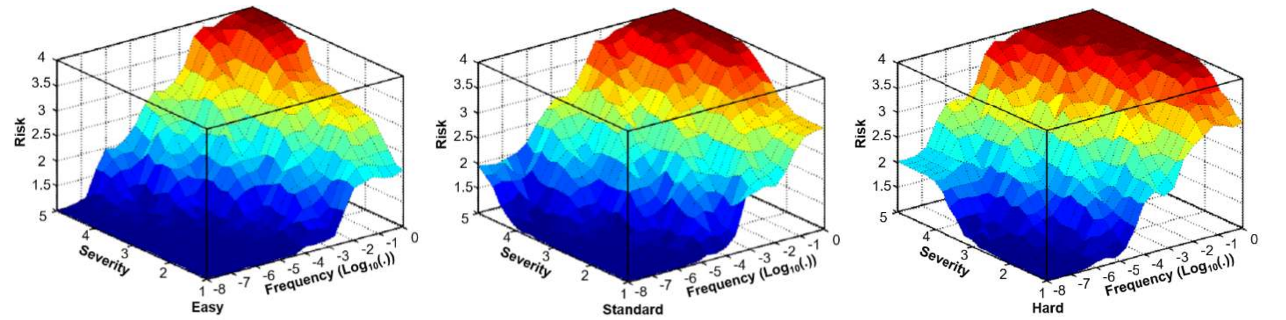

FIGURE 6. 3-Dim risk surface from different types of inference rules.

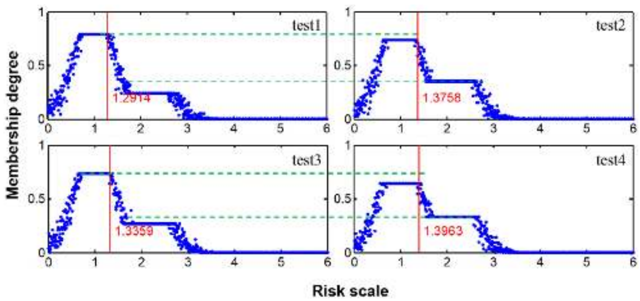

FIGURE 7. Comparison of results from multiple calculations.

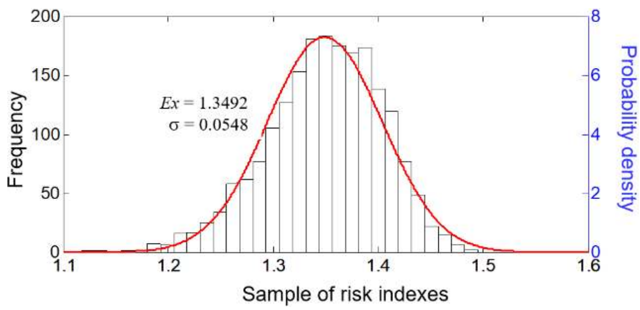

FIGURE 8. Probability density function and frequency histogram of samples.

analyzed. Considering the "Standard" type inference rules, the cloud risk matrix is implemented four times, and the comprehensive risk cloud and risk index are shown in Fig. 7.

Under the same condition of input variables and inference rules, there are some differences in these comprehensive risk clouds and risk indexes. The blue part in each figure shows the distribution of random cloud droplets where there are two steps with different heights. The comprehensive risk index obtained by defuzzification is also different, of which the data range is [1.2914,1.3963] with a difference of less than 10%. Therefore, the calculation process and risk index results reflect certain randomness.

The main reason for the above phenomenon is that the cloud model can consider the fuzziness and randomness of linguistic terms at the same time. Given the frequency index and consequence index of the evaluation object, the membership calculation of each variable grade is no longer a

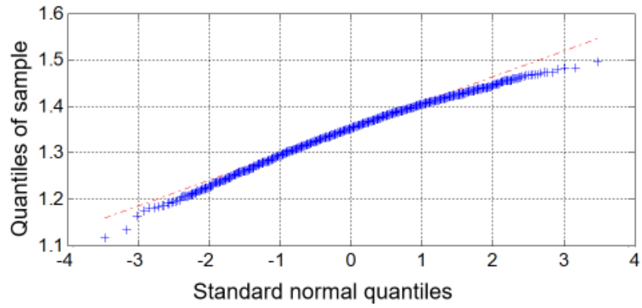

FIGURE 9. Q-Q plot for samples of risk indexes.

certain value, but a random value in a certain range according to the characteristic parameters of the cloud model. After the rule-based inference process, the random membership value is transferred to the comprehensive risk cloud model, resulting in some differences in the height of "steps" in Fig. 7. During the production process of the integrated cloud model, a large number of numerical values are obtained uniformly or randomly in the risk index domain to calculate the random membership degree, and the uncertainty in the linguistic terms of risk level is considered resulting in the randomness of the location of cloud droplets. Therefore, the comprehensive risk cloud and risk index have certain randomness.

D. DISTRIBUTION OF THE RANDOM RESULTS

Through sample statistics, the results of the risk index from a number of $N = 2000$ calculations for RAS(R)1 based on cloud risk matrix are statistically analyzed. The expectation and standard deviation of the sample of risk index r_i are $Ex = 1.3492$ and $\sigma = 0.0548$ respectively. The probability density function of normal based on Ex and σ is plotted by the red line in Fig. 8. Meanwhile, the frequency histogram of the risk index is also illustrated, as shown in the black bar. As can be seen that the results of the risk index well meet the normal distribution, and the risk index values fluctuate randomly with expectation as the center.

A quantile graph, also called a Q-Q plot, is an effective statistical tool used to test the distribution of sample data [42]. It can visually analyze the correlation between sample data and target distribution to verify whether the sample data meet the target distribution. As for the quantile plot for normal

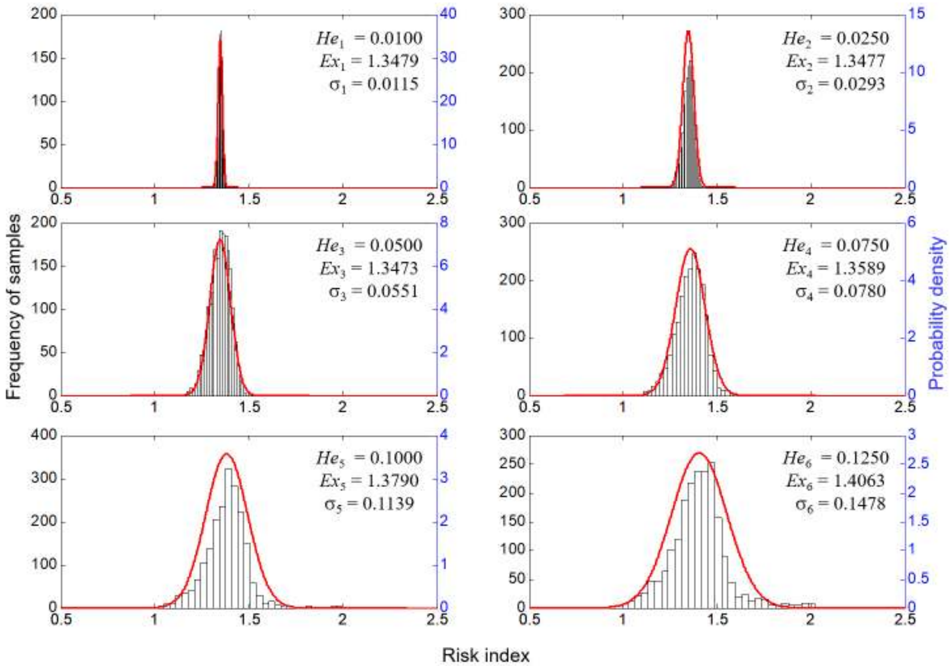

FIGURE 10. Frequency histogram and normal probability density function for different *He*.

distribution, if the distribution of scattered points in the image is close to a straight line, it means that the sample data follows the normal distribution, and the intercept of the straight line in the coordinate system is the expectation of the sample data, and the slope of the straight line is the standard deviation of the sample data. On the contrary, if the scatter distribution deviates greatly from the linear form, the sample data does not obey the normal distribution.

In this paper, risk indexes r_i obtained are taken as sample data, and normal distribution Q-Q diagram is drawn to verify the distribution characteristics of sample data, as shown in Fig. 9. The blue mark is the quantile formed by the sample data, and the red dotted line represents the trend line close to the sample data. It can be seen that the distribution of the sample data is similar to the straight line, and there is only a small deviation at both ends. This phenomenon shows that the calculated risk index values obey the normal distribution well under the current conditions.

The intercept of the red trend lines is approximately 1.35, and the expected value obtained from the sample data statistics is 1.3492, as shown in Fig. 8. The risk index calculated by the fuzzy risk matrix method is 1.35, given in TABLE 2. The similarity of these values suggests the effectiveness and rationality of the results from the cloud risk matrix. The randomness is introduced to allow a certain degree of fluctuation around the expected values which are consistent with the results from the fuzzy risk matrix.

E. EFFECT OF THE HYPERENTROPY HE

The critical characteristic number hyperentropy *He* determines the thickness of the cloud and the randomness degree of membership for each linguistic variable which brings the randomness of the risk index. It is necessary to investigate the effect of the initial defined hyperentropy *He* on the volatility of risk assessment results. Several specific values of the hyperentropy *He* are selected, including $He_1 = 0.01$, $He_2 = 0.025$, $He_3 = 0.05$, $He_4 = 0.075$, $He_5 = 0.1$, $He_6 = 0.125$, to carry out 2000 independent repeated trials respectively using the cloud risk matrix. The frequency histogram and normal probability density function are plotted according to the data results, as shown in Fig. 10.

As can be seen from Fig. 10, the increase of the hyperentropy value *He* leads to a larger value of the standard deviation, the sample data is distributed in a wider range, and the randomness of the risk index results is stronger. At the same time, the sample expected value has a large deviation when *He* is large, such as $He_5 = 0.1$ and $He_6 = 0.125$.

The statistical result of risk indexes under different hyperentropy *He* is drawn into a Q-Q plot, as shown in Fig. 11. As can be seen that when the hyperentropy *He* is small ($He = 0.01, 0.025, 0.05, 0.075$), the scattered points in the graph are close to a straight line, indicating that the risk index results follow the normal distribution. When the hyperentropy *He* becomes larger ($He = 0.1, 0.125$), the middle part of the scatters is close to the straight line, but there is obvious deviation at both ends, indicating that the statistical data of the risk index no longer meet the normal distribution.

It can be concluded from the above appearance that the hyperentropy *He* is the key index that affects the fluctuation range of risk index results. *He* is positively correlated with the fluctuation range, and the standard deviation of risk index samples increases with the increase of *He*. However, when

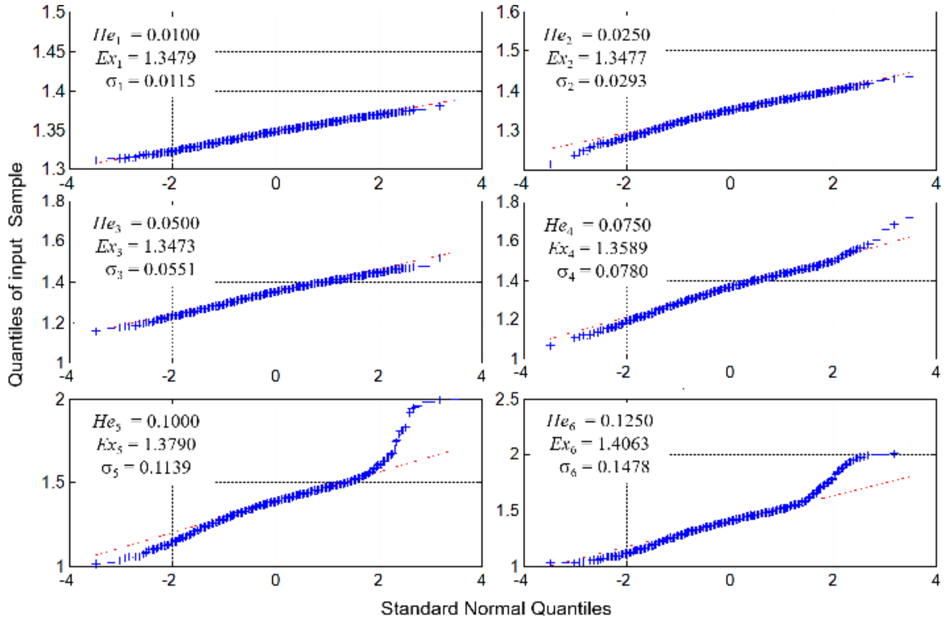

FIGURE 11. Quantiles plot for different *He*.

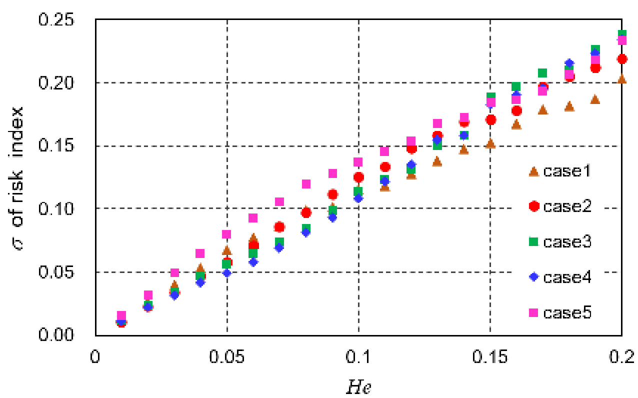

FIGURE 12. Relationship between the standard deviation of risk index and hyperentropy.

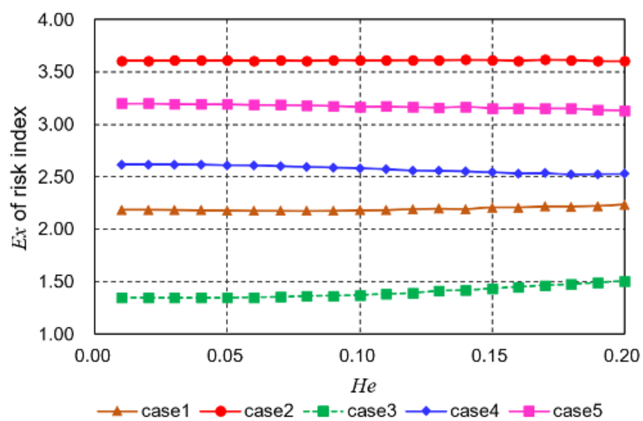

FIGURE 13. Relationship between the expectation of risk index and hyperentropy.

the hyperentropy *He* exceeds a certain limit, there is a big gap between the distribution of statistical samples and the normal distribution. And also, it will affect the stability of sample expectations.

For the further investigation of the effect of hyperentropy *He* on the risk index, the relationship between the expectation, the standard deviation of risk indexes, and the several values of *He* in the domain of (0, 0.2] are discussed. for several cases with different input values as shown in TABLE 3, as shown in Fig. 12 and Fig. 13. It is worth noting that these cases involve different combinations of probability levels and severity levels for more extensive effectiveness.

It can be seen from Fig. 12 that under different frequency-severity combinations, the standard deviation σ of risk index and hyperentropy He presents a positive linear relationship that the σ increases linearly with that of hyperentropy. Therefore, in the initial stage of the cloud risk matrix, the two factors can be approximately regarded as a positive proportional relationship according to the decision maker's acceptance of the fluctuation range of the risk index results, to determine the selection of hyperentropy He in the cloud model for each variable levels.

TABLE 3. Cases with different input values.

	case1	case2	case3	case4	case5
Frequency index f_0	-4.2	-2.4	-6.84	-2.4	-2.4
Severity index s_0	3.2	4.35	4.35	1.7	3.2

Fig. 13 suggests the hyperentropy *He* has a slight influence on the expectation *Ex* of risk index, and the latter maintains the overall stability within a large range of *He*. However, when *He* exceeds 0.1, the expectation *Ex* of case 1, case 3, case 4, and case 5 deviate obviously, and the deviation direction is not consistent. Therefore, considering the stability of the risk index results and the rationality of random fluctuations, it is suggested that the value of hyperentropy He should not exceed 0.1 during the determination of cloud models. Meanwhile, the selection of $He = 0.05$ in the above case study can be proved to be effective and reasonable.

VI. CONCLUSION

In this paper, a novel cloud risk matrix approach based on the expert knowledge and inference rules is presented for the risk assessment of process safety considering the epistemic uncertainty in experts cognition. It provides a new strategy to express the linguistic variables both in the frequency of accident and the severity of consequence in a mathematical manner by employing the cloud model theory. A case study for the risk assessment of a distillation column unit has been performed based on the proposed cloud risk matrix, and the results are compared with that from the fuzzy risk matrix, which indicates the effectiveness and rationality of the proposed method in dealing with the epistemic uncertainty in the linguistic assessment.

The source and key impact factors of the randomness in the risk index are discussed in this paper and the statistical property analysis of the assessment results is carried out. The effect of hyperentropy He on the distribution of assessment result is investigated that the hyperentropy He presents a positive linear relationship with the standard deviation σ of risk index, while with a slight influence on the expectation Ex. The main conclusions include the following aspects:

(1) The proposed cloud model-based Mamdani inference algorithm and the improved centroid algorithm can effectively handle the random membership in the form of discrete cloud drops. The inference and defuzzification process based on knowledge rules can be carried out and provide the quantitative risk assessment result.

(2) Based on abundant repeated calculations, the results of the risk index are statistically analyzed. The randomness introduced in the description of linguistic variables in grade concept results in certain randomness and volatility of risk index, of which the statistical data meet the normal distribution.

(3) The sensitivity analysis of hyperentropy He of the cloud model shows that the fuzzy risk matrix method is a special form of cloud risk matrix method when He is zero, and the cloud risk matrix is an extension of the fuzzy risk matrix method considering the randomness of membership degree. Statistical analysis indicates that the standard deviation σ of the risk index has an approximately positive relationship with the hyperentropy He so that the choice of the hyperentropy He in the cloud risk matrix can be determined according to the decision maker's acceptance of the fluctuation range of the risk index. The expectation Ex of risk index will have obvious deviation when the hyperentropy He is defined as a larger value. To ensure the stability and reliability of the results, it is suggested that the hyperentropy He should not be more than 0.1.

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