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Cloud Model-Based Intelligent Evaluation Method in Marine Engine Room Simulator

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ABSTRACT With the implementation of the new international conventions, higher evaluation requirements for a marine engine room simulator have been put forward. Based on the cloud theory, an improved fuzzy comprehensive evaluation method was studied: First, the Delphi method was adopted to get the original cloud drops of the judgments, and the original judgment weight clouds were generated by the backward cloud generator. Second, the judgment cloud matrix was built using the comparison results of the original judgment weight clouds, and the cloud weights of the evaluation factors were further calculated. Third, the appraisal grade clouds were generated, and the cloud appraisal vector taking into account the importance of each factor for each appraisal grade was calculated. Finally, the evaluation cloud result E was aggregated, and the similarity vector between E and the grade clouds was calculated. The calculation process reflects an effective uncertainty conversion between a qualitative concept and quantitative characteristics. The effectiveness was verified using three interrelated examples. The results show the following: the expectation of E is mainly determined by the operating process and, second, by the expectation of the cloud weights; the uncertainty index and the randomness index of E are determined by the parameter values of the cloud weights and the impact of the closest grade cloud; and the similarity vector is directly affected by E and the distribution of the grade clouds. The introduction of cloud model theory into fuzzy comprehensive evaluation is an effective evaluation method.

INDEX TERMS Marine engineering, cloud model theory, intelligent evaluation, engine room simulation.

I. INTRODUCTION

The existing evaluation methods of the marine Engine Room Simulator (ERS) mainly focus on the degree of task completion and only give a quantitative value as the evaluation result. The result cannot reflect the uncertainty of experts' judgments. In fact, uncertainty is inevitable; therefore, it is necessary for these methods to give more meaningful quantitative analysis results. With the implementation of the new international conventions, higher requirements for the accuracy and objectivity of the evaluation system for an ERS have been put forward. Therefore, an effective intelligent evaluation method has become a research hotspot in ERSs. Intelligent evaluation is an upgraded model of the electronic automated evaluation. There are generally three types of research methods on intelligent assessment [1]: adopt computer science to simulate the functions of the human brain; research the evaluation activities of the human brain from the perspective of physiology; and combine the above two and associate probability theory with evolutionary theory. With the help of Artificial Intelligence (AI), computers can think and act humanly and rationally [2]. Intelligent evaluation, which usually refers to the ability of a computer equipped with AI to learn a specific task from data or experimental observation, is an application from computational intelligence. The application of computational intelligence in marine engineering area has been shown to be useful.

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A. INTELLIGENT EVALUATION IN MARINE OPERATIONS

To formulate human experts' domain experience and marine engineering safety knowledge, Sii *et al.* [3] used the fuzzy logic and adaptive-fuzzy-logic approaches to conduct risk analysis and to transform the different properties from various sources to the knowledge base. In addition, Ren *et al.* [4] used the fuzzy reasoning and evidential synthesis approaches to propose an offshore safety assessment framework, which can deal with uncertainties, including ignorance and vagueness. Ikenishi *et al.* [5] used a desktop engine simulator to complete an assessment for trainers in groups and found that effective collaborative training can reduce the human errors in actual work. Panagiotis and Nikitas [6] improved an evaluation method in the maritime teaching process and combined it with a simulator to carry out simulation training and assessment. Nie *et al.* [7] set up a scoring mathematical model of an ERS and combined it with the fuzzy comprehensive evaluation method and the expert system theory to achieve an automatic scoring calculation. Based on the fuzzy comprehensive evaluation method, Cao *et al.* [8] designed and developed an automatic evaluation system of an ERS to assess the specified items according to a practice exam outline. Hu *et al.* [9] analyzed the factors affecting the operating ability of an ERS and studied modeling methods to improve the assessment in the training of ship power systems. Duan *et al.* [10] adopted different methods to calculate and optimize the weights, proposed two intelligent assessment methods based on the expert system and machine learning, and conducted a comparative analysis of the two methods. Shen *et al.* [11] designed a virtual engine room training and evaluation system based on the fuzzy comprehensive evaluation method and verified it using a 3D virtual engine room. Duan *et al.* [12] used the genetic algorithm and game theory strategy to optimize the weights of the evaluation factors and designed an evaluation system for an ERS.

B. INTELLIGENT EVALUATION IN OTHER FIELDS

Fan *et al.* [13] used simulation data to discretely quantize the driving technology specified in a training program and established an evaluation model to evaluate the flight quality. Yang [14] obtained sample data through a questionnaire survey, established a management evaluation model based on the BP artificial neural network, and verified the evaluation effect. Chang *et al.* [15] integrated the analytic hierarchy process, performance analysis and the binary fuzzy language representation model to evaluate the effectiveness of a soldier combat training simulator system. To construct a track evaluation index system, Fang *et al.* [16] established a single ship inward and outward port evaluation model for a ship-handling simulator and proposed a similarity evaluation algorithm based on the 2D normal cloud model parameters. For the rescue training of helicopter crews in a simulated environment, Sun *et al.* [17] regarded the complex training process as an interaction system of the discrete event and activity flow and implemented a training simulation assessment method based on virtual simulation. Ren *et al.* [18] used the extreme learning machine method as a data learning tool and built a data-driven evaluation model to carry out data learning for the efficiency evaluation. Aiming at the problems of subjectivity and uncertainty when making combat capability assessment plans, Wang *et al.* [19] combined expert experience and a self-learning algorithm to propose an adaptive fuzzy wavelet neural network collaborative combat capability evaluation model. Li *et al.* [20] combined the expert knowledge and experience in training plans through a questionnaire, weight enhancement and similarity calculation and proposed a new method to evaluate the visual attention in maritime action. Based on the decision-making chain of UAV cooperative combat, Huang and Zhou [21] established an evaluation model of UAV collaborative combat effectiveness by considering multiple collaboration capabilities.

C. AIM AND CONTRIBUTIONS

An effective intelligent evaluation method in ERSs can promote the competency assessment of crew. In the existing evaluation methods of an ERS, once the weights obtained through the experts' judgments are determined, the uncertainty and randomness are lost. This makes the evaluation results have strong absoluteness and further makes it more difficult to objectively express an evaluation result. Therefore, based on the existing methods, this paper aims to realize quantitative analysis incorporating the uncertainty and randomness in the evaluation process to obtain a quantitative result related to the degree of a task's completion and a qualitative result related to the appraisal grades.

By introducing cloud theory to the existing evaluation methods of ERSs, the following contributions are made:

i. The more meaningful result parameters such as the expectation, uncertainty, randomness, and similarity can be obtained, and these have never been considered in existing evaluations;

ii. Quantitative analysis can be carried out to verify that the fuzziness of the evaluation result is derived from the uncertainty and randomness of the cloud weights and the appraisal grades;

iii. A calculated cloud similarity vector can be used to get a qualitative result, which represents the similarities between the evaluation result and the divided appraisal grades.

II. PROPOSED METHODOLOGY

The methodology elaborated in this paper includes three main phases: cloud evaluation initialization (phase one), which is responsible for determining the associated evaluation factors, the cloud appraisal grades, and the fuzzy membership functions; weight cloud calculation (phase two), which is responsible for calculating the judgment weight cloud, the judgment cloud matrix, and the cloud weight vector; and cloud evaluation calculation (phase three), which is responsible for constructing the fuzzy mapping matrix and the cloud appraisal vector and getting the evaluation result after the evaluation operation is submitted. The flowchart of the proposed methodology is presented in Fig. 1. The methods involved in each stage are as follows.

A. CLOUD MODEL METHOD

To eliminate the fuzziness and randomness inherent in human cognition, we assume that U is the quantitative domain

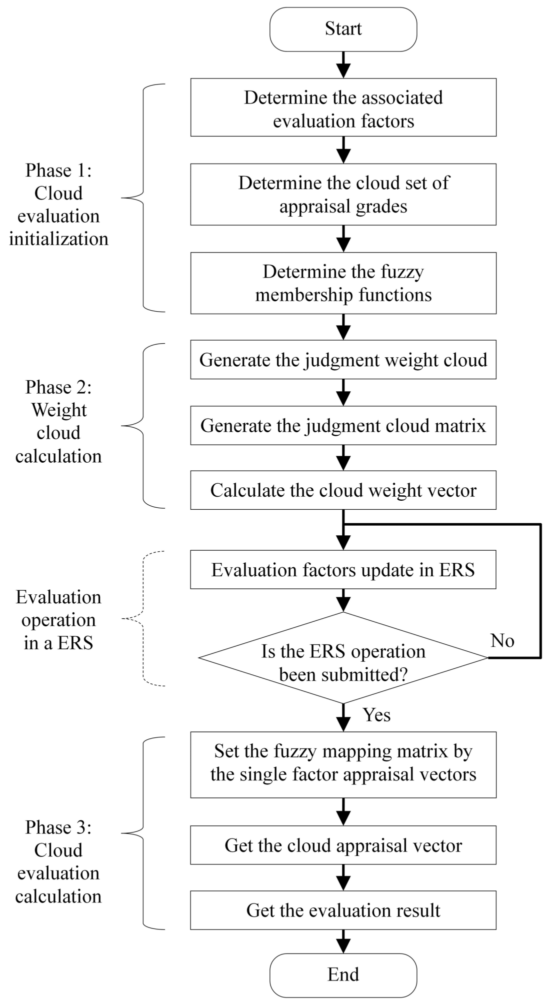

FIGURE 1. Visual representation of the proposed methodology.

expressed by accurate numbers and C is a qualitative concept in U. There is a corresponding degree of certainty $\mu(x)$ to C for an arbitrary $x \in U$. The Cloud Model (CM) can be defined by (1).

$$\mu : U \rightarrow [0, 1], \quad \forall x \in U, \quad x \rightarrow \mu(x) \tag{1}$$

where x is a random realization of the qualitative concept C; $\mu(x)$ is a random number with a stable tendency, which called the degree of membership of x to C; and (x, μ) is called the cloud drop [22].

1) DIGITAL FEATURES OF THE CM

A CM can be described as $C(Ex, En, He)$ with three numerical characters Ex, En, and He. Ex is the expected value or the mean of a qualitative concept, which best represents the qualitative concept. En is called the entropy, and it is the uncertainty distribution of the concept representing the range of values that could be accepted in the domain. In addition, En reflects the fuzziness of the qualitative concept, and it can be used to measure the randomness of cloud drops; therefore, the larger En is, the larger the fuzziness and randomness of the concept. He is called the hyperentropy, and it is a measure of the randomness and fuzziness of the entropy En. He can be used to reflect the dispersion of cloud drops and determine the thickness of the cloud directly. The larger He is, the greater the degree of dispersion, the greater the randomness of the degree of membership, and the thicker the cloud [23].

There are different kinds of CMs, such as the Gauss cloud, trapezium cloud, half-down cloud, half-up cloud and so on [24]. Among them, the Gauss CM plays a prominent role in this application due to its universality and stability [25], and it can be described as follows:

$$\begin{cases} x \sim N(Ex, En'^2) \\ En' \sim N(En, He^2) \end{cases} \tag{2}$$

$$y = \mu(x) = \exp\left(\frac{-(x - Ex)^2}{2En'^2}\right) \tag{3}$$

If En' is replaced by its expectation En in (3), the CM will degenerate into the CM's expectation curve as

$$y = \mu(x) = \exp\left(\frac{-(x - Ex)^2}{2En^2}\right) \tag{4}$$

In addition, according to the 3σ rule, let $2En^2 = 2(En + kHe)^2$ in (4). Then, the entropy expectation function of the CM can be derived as

$$y = \mu(x) = \exp\left(\frac{-(x - Ex)^2}{2(En + kHe)^2}\right), \quad k \in [-3, 3] \tag{5}$$

where k is called the entropy expectation parameter.

For a more intuitive representation, two approximate shapes of Gauss clouds $C(0, 0.5, 0.1)$ and $C(0, 0.3, 0.08)$ with 700 cloud drops and their entropy expectation curves are illustrated as an example in Fig. 2.

2) CLOUD GENERATOR

A cloud generator can establish a mapping relationship between a qualitative concept and a quantitative

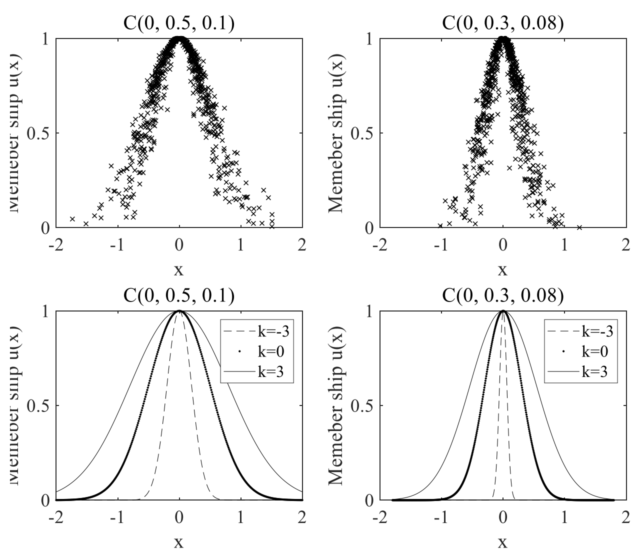

FIGURE 2. Two CMs with the entropy expectation curves.

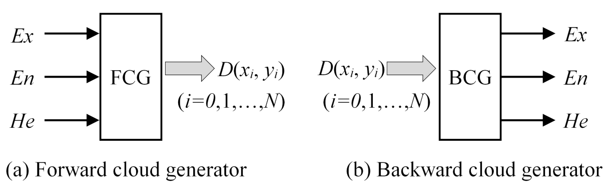

FIGURE 3. **Cloud generators.**

characteristic. There are two primary kinds of generators [26], as seen in Fig. 3, namely, the forward cloud generator (FCG) and the backward cloud generator (BCG).

a: FORWARD CLOUD GENERATOR

As seen in Fig. 3(a), the FCG can map a qualitative concept to quantitative characteristics within the required number of cloud drops $D(x_i, y_i)$ using the three given numerical characters Ex, En, and He. The mapping is a forward and direct process, and the FCG algorithm is shown as follows:

Step 1: Determine qualitative concept and the parameters.

Determine qualitative concept C and get the corresponding parameter values Ex, En, and He. Set the number N of cloud drops. Take Ex, En, He, and N as the input parameters of the FCG.

Step 2: Generate a normally distributed random number.

Generate a normally distributed random number En'_i with a mean of En and a standard deviation of He and further generate a normally distributed random number x_i with a mean of Ex and a standard deviation of En'_i.

Step 3: Generate a cloud drop.

Use x_i as a specific quantitative value of qualitative concept C, and calculate y_i using (3). y_i is the degree of membership of x_i to C. $D(x_i, y_i)$ is a cloud drop generated in this loop, and it reflects a qualitative to quantitative transformation.

Step 4: Get the output parameters of the FCG.

Repeat Step 2 and Step 3 until $i = N$, and this means that N cloud drops are generated. The quantitative value x_i ($i = 0, 1, \ldots, N$) of qualitative concept C and the degree of membership y_i ($i = 0, 1, \ldots, N$) are the output parameters of the FCG.

b: BACKWARD CLOUD GENERATOR

Contrary to the FCG, as seen in Fig. 3(b), the BCG can map quantitative characteristics to a qualitative concept C, where the three quantitative characteristics Ex, En, and He can be used to represent the corresponding qualitative concept C from a given cloud drop sample. The mapping is a reverse and indirect process, and the BCG algorithm is calculated as follows:

Step 1: Calculate the estimate of Ex.

Calculate the sample mean $\hat{E}x$ based on x_i via (6), and take x_i as an estimate of Ex.

$$\hat{E}x = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{6}$$

Step 2: Check the effectiveness of the cloud drops.

Check the effectiveness of the cloud drops by removing the cloud drops with $y_i > 0.999$ [27], and suppose that the number of cloud drops left is M.

Step 3: Calculate the estimate of En.

Put x_i into (7) to get En'_i, and further put En'_i into (8) to get $\hat{E}n$, which is the estimate of En.

$$En'_i = \frac{|x - \hat{E}x|}{-\sqrt{2\ln y_i}}, \quad i = 0, \cdots, M \tag{7}$$

$$\hat{E}n = \frac{1}{M}\sum_{i=1}^{M} En'_i \tag{8}$$

Step 4: Calculate the estimate of He.

Calculate $\hat{H}e$ as the estimate of He via (9).

$$\hat{H}e = \sqrt{\frac{1}{M-1}\sum_{i=1}^{M}(En'_i - \hat{E}n)^2} \tag{9}$$

Step 5: Get the output parameters of BCG.

The calculated $\hat{E}x$, $\hat{E}n$, and $\hat{H}e$ are the output parameters of the BCG, which reflect a quantitative to qualitative mapping.

3) CLOUD ALGORITHM

Let $C_1(Ex_1, En_1, He_1)$ and $C_2(Ex_2, En_2, He_2)$ be two clouds, and the arithmetic and power operation of C_1 and C_2 are calculated as follows [28]:

$$C_1 \pm C_2 = C_{1\pm 2}(Ex_1 \pm Ex_2, \sqrt{En_1^2 + En_2^2}, \sqrt{He_1^2 + He_2^2}) \tag{10}$$

$$\begin{aligned} C_1 \times C_2 = C_{1\times 2}\Bigg(&Ex_1Ex_2, |Ex_1Ex_2|\sqrt{\left(\frac{En_1}{Ex_1}\right)^2 + \left(\frac{En_2}{Ex_2}\right)^2}, \\ &|Ex_1Ex_2|\sqrt{\left(\frac{He_1}{Ex_1}\right)^2 + \left(\frac{He_2}{Ex_2}\right)^2}\Bigg) \end{aligned} \tag{11}$$

$$\lambda C_1 = C_{\lambda 1}\left(\lambda Ex_1, \sqrt{\lambda}En_1, \sqrt{\lambda}He_1\right), \quad \lambda \geq 0 \tag{12}$$

$$\begin{aligned} \frac{C_1}{C_2} = C_{\frac{1}{2}}\Bigg(&\frac{Ex_1}{Ex_2}, \left|\frac{Ex_1}{Ex_2}\right|\sqrt{\left(\frac{En_1}{Ex_1}\right)^2 + \left(\frac{En_2}{Ex_2}\right)^2}, \\ &\left|\frac{Ex_1}{Ex_2}\right|\sqrt{\left(\frac{He_1}{Ex_1}\right)^2 + \left(\frac{He_2}{Ex_2}\right)^2}\Bigg) \end{aligned} \tag{13}$$

$$(C_1)^m = C_1^m\left(Ex_1^m, \sqrt{m}Ex_1^{m-1}En_1, \sqrt{m}Ex_1^{m-1}He_1\right) \tag{14}$$

The concepts of C_1 and C_2 must be in the same universe of discourse so that the CM operation involved in the algorithm above has meaning. The CM arithmetic operation will be simplified as the algorithm between the CM and a precise value when either the entropy En or hyperentropy He is zero or both are zero.

4) NORMAL CM SIMILARITY CALCULATION

In the qualitative evaluation activities, the traditional method takes the expectation Ex of the comprehensive cloud as the reference. If Ex is in the range of an appraisal grade, then it can be considered as belonging to the appraisal grade. However, if Ex is between two appraisal grade boundaries, the evaluation result will have strong subjective randomness. Therefore, the CM similarity calculation method should be considered.

Let $C_1(Ex_1, En_1, He_1)$ and $C_2(Ex_2, En_2, He_2)$ be two clouds, and the similarity S_{12} of the two clouds can be comprehensively calculated using the shape similarity S_{S12} and position similarity S_{P12} [29]:

The shape similarity S_{S12} can be calculated by

$$S_{S12}(C_1, C_2) = \frac{\min\left((En_1 + 3He_1)/En_1, (En_2 + 3He_2)/En_2\right)}{\max\left((En_1 + 3He_1)/En_1, (En_2 + 3He_2)/En_2\right)} \tag{15}$$

The position similarity S_{P12} can be calculated by

$$S_{P12}(C_1, C_2) = p_{over}/p_{total} \tag{16}$$

where

$$p_{over} = \begin{cases} \min(Ex_1 + 3En_1, Ex_2 + 3En_2) \\ \quad - \max(Ex_1 - 3En_1, Ex_2 - 3En_2) \\ 0 \quad if \quad p_{over} < 0 \end{cases} \tag{17}$$

$$p_{total} = \max(Ex_1 + 3En_1, Ex_2 + 3En_2) - \min(Ex_1 - 3En_1, Ex_2 - 3En_2) \tag{18}$$

Then, the cloud similarity S_{12} can be calculated by

$$S_{12}(C_1, C_2) = S_{S12}(C_1, C_2) \cdot S_{P12}(C_1, C_2), \quad S_{12} \in [0, 1] \tag{19}$$

B. WEIGHT CLOUD CALCULATION

The Delphi method that collects experts' repeated independent subjective judgments can be used to obtain relatively objective information [30]. To keep the fuzziness of expert judgments, we combine cloud theory with the Delphi method to provide a mapping of quantitative appraisal values to qualitative judgments. The judgments generated by the Delphi method are used as the original cloud drops to generate the weight clouds via the BCG. The calculation steps are as follows:

Step 1: Generate the original judgment weight cloud.

Adopt the Delphi method to collect the assessments of experts for each evaluation factor in the form of a given dimensionless range and repeatedly feedback the average values associated with the opinions of the previous judgments of the experts to the next investigative round until the judgments are satisfied or the maximum number of investigative rounds are conducted [31], [32]. The investigation results will form dataset vector $\boldsymbol{P}$ according to the evaluation factors, and $\boldsymbol{P}$ is shown as

$$\boldsymbol{P} = (\boldsymbol{p}_1, \boldsymbol{p}_2, \cdots, \boldsymbol{p}_n) \tag{20}$$

where n is the number of evaluation factors for an assessment item, and $\boldsymbol{p}_i$ $(i = 0, 1, \ldots, n)$ is the expert judgment set of evaluation factor i.

Using $\boldsymbol{P}$, we adopt the BCG algorithm with steps 1 to 5 to generate the original judgment weight clouds as

$$C_P = (C_{P1}, C_{P2}, \cdots, C_{Pn}) \tag{21}$$

$$C_{Pi} = C_{Pi}(Ex_{Pi}, En_{Pi}, He_{Pi}), \quad i = 0, 1, \cdots, n \tag{22}$$

where C_{Pi} is the judgment weight cloud of evaluation factor i.

Step 2: Establish a hierarchical structure mode.

Set the top layer as the target layer of an assessment item and the bottom layer as the evaluation factor layer. In the analysis of a complex evaluation item, more layers need to be built, and the steps are similar [33].

Step 3: Construct the judgment cloud matrix.

Let $\boldsymbol{A}$ be the judgment cloud matrix. Then

$$\boldsymbol{A} = \begin{bmatrix} C_{11}(Ex_{11}, En_{11}, He_{11}) & C_{12}(Ex_{12}, En_{12}, He_{12}) & \cdots & C_{1n}(Ex_{1n}, En_{1n}, He_{1n}) \\ C_{21}(Ex_{21}, En_{21}, He_{21}) & C_{ij}(Ex_{22}, En_{22}, He_{22}) & \cdots & C_{2n}(Ex_{2n}, En_{2n}, He_{2n}) \\ \vdots & \vdots & \cdots & \vdots \\ C_{n1}(Ex_{n1}, En_{n1}, He_{n1}) & C_{n2}(Ex_{n2}, En_{n2}, He_{n2}) & \cdots & C_{nn}(Ex_{nn}, En_{nn}, He_{nn}) \end{bmatrix} \tag{23}$$

where n is the number of evaluation factors, and the cloud element C_{ij} of A is the comparison result of the original judgment weight clouds C_{Pi} and C_{Pj}. The comparison method is

$$C_{ij}(Ex_{ij}, En_{ij}, He_{ij}) = \begin{cases} \dfrac{C_{Pi}(Ex_{Pi}, En_{Pi}, He_{Pi})}{C_{Pj}(Ex_{Pj}, En_{Pj}, He_{Pj})}, & i \neq j \\ C_{ij}(1, 0, 0), & i = j \end{cases} \tag{24}$$

and by referring to (13) and (24), C_{ij} can be derived as

$$C_{ji} = \begin{cases} Ex_{ji} = \dfrac{1}{Ex_{ij}} \\ En_{ji} = \dfrac{En_{ij}}{Ex_{ij}^2} \\ He_{ji} = \dfrac{He_{ij}}{Ex_{ij}^2}, \end{cases} \quad C_{ji} = \frac{1}{C_{ij}} \tag{25}$$

Step 4: Calculate the cloud weight vector.

The square root method can be adopted to obtain the cloud weight vector $\boldsymbol{W}$ from the judgment cloud matrix $\boldsymbol{A}$ as follows:

Let the cloud weight vector $\boldsymbol{W}$ be

$$\boldsymbol{W} = (C_{w1}, C_{w2}, \ldots, C_{wn}) \tag{26}$$

where

$$C_{wi} = C_{wi}(Ex_{wi}, En_{wi}, He_{wi}), \quad i = 0, 1, \cdots, n \tag{27}$$

Then based on (11), three numerical characters Ex_{wi}, En_{wi}, and He_{wi} of cloud weight C_{wi} can be calculated [34] by

$$r_i = \left(\prod_{j=1}^{n} C_{ij}\right)^{\frac{1}{n}} \tag{28}$$

TABLE 1. The numerical characters of cloud appraisal grades.

Grade cloud	Ex	En	He
$C_{v-k}(Ex_{v-k}, En_{v-k}, He_{v-k})$	x_{min}	$En_{v-k+1}/0.618$	$He_{v-k+1}/0.618$
$C_{v-k+1}(Ex_{v-k+1}, En_{v-k+1}, He_{v-k+1})$	$x_{min}+3En_{v-k+1}$	$En_{v-k+2}/0.618$	$He_{v-k+2}/0.618$
$C_{v-k+2}(Ex_{v-k+2}, En_{v-k+2}, He_{v-k+2})$	$Ex_{v-k+3}-0.382(Ex_{v-k+3}-Ex_{v-k+1})$	$En_{v-k+3}/0.618$	$He_{v-k+3}/0.618$
…	…	…	…
$C_{v-1}(Ex_{v-1}, En_{v-1}, He_{v-1})$	$Ex_{v0}-0.382(Ex_{v0}-Ex_{v-k+1})$	$En_{v0}/0.618$	$He_{v0}/0.618$
$C_{v0}(Ex_{v0}, En_{v0}, He_{v0})$	$(x_{min}+x_{max})/2$	$0.382(x_{max}-x_{min})/3(m-1)$	$En_{v0}/2$
$C_{v+1}(Ex_{v+1}, En_{v+1}, He_{v+1})$	$Ex_{v0}+0.382(Ex_{v+k-1}-Ex_{v0})$	$En_{v0}/0.618$	$He_{v0}/0.618$
…	…	…	…
$C_{v+k-2}(Ex_{v+k-2}, En_{v+k-2}, He_{v+k-2})$	$Ex_{v+k-3}+0.382(Ex_{v+k-1}-Ex_{v+k-3})$	$En_{v+k-3}/0.618$	$He_{v+k-3}/0.618$
$C_{v+k-1}(Ex_{v+k-1}, En_{v+k-1}, He_{v+k-1})$	$x_{max}-3En_{v+k-1}$	$En_{v+k-2}/0.618$	$He_{v+k-2}/0.618$
$C_{v+k}(Ex_{v+k}, En_{v+k}, He_{v+k})$	x_{max}	$En_{v+k-1}/0.618$	$He_{v+k-1}/0.618$

and then

$$C_{wi} = C_{wi}(Ex_{wi}, En_{wi}, He_{wi}) = r_i / \sum_{i=0}^{n} r_i \tag{29}$$

C. CLOUD EVALUATION CALCULATION

Using the cloud weight vector calculated above, the improved fuzzy comprehensive calculation based on the CM can be used evaluate the given tasks in an ERS [35]. The steps are as follows:

Step 1: Determine the set of evaluation factors.

$$\boldsymbol{U} = \{u_1, u_2, \ldots, u_n\} \tag{30}$$

where u_i ($i = 0,\ldots, n$) is evaluation factor i with varying degrees of fuzziness.

Step 2: Determine the cloud set of appraisal grades.

Let the appraisal grades be m, and set an effective appraisal domain $[x_{\min}, x_{\max}]$ to generate m appraisal grade clouds [36], which are used to represent the cloud set of appraisal grades $\boldsymbol{V}_C$

$$\boldsymbol{V}_C = \{C_{v1}, C_{v2}, \ldots, C_{vm}\} \tag{31}$$

$$C_{vj} = C_{vj}(Ex_{vj}, En_{vj}, He_{vj}), \quad j = 0, 1, \ldots, m \tag{32}$$

where C_{vj} represents one appraisal grade cloud among the appraisal grades. Therefore, the appraisal grade vector can be described as

$$\boldsymbol{V}_C(Ex) = (Ex_{v1}, Ex_{v2}, \ldots, Ex_{vm}) \tag{33}$$

Generally, the number of appraisal grades m is odd, and can be expressed as

$$m = 2k + 1, \quad k >= 0 \tag{34}$$

In addition, if we let the middle appraisal cloud be $C_{v0}(Ex_{v0}, En_{v0}, He_{v0})$, the left adjacent clouds be from C_{v-1}, $C_{v-2},\ldots, C_{v-k}$, and the right adjacent clouds be from C_{v+1}, $C_{v+2},\ldots, C_{v+k}$, then the cloud set of appraisal grades can be expressed as

$$\boldsymbol{V}_C = \begin{cases} C_{v-k}(Ex_{v-k}, En_{v-k}, He_{v-k}) \\ \quad\cdots \\ C_{v-1}(Ex_{v-1}, En_{v-1}, He_{v-1}) \\ C_{v0}(Ex_{v0}, En_{v0}, He_{v0}) \\ C_{v+1}(Ex_{v+1}, En_{v+1}, He_{v+1}) \\ \quad\cdots \\ C_{v+k}(Ex_{v+k}, En_{v+k}, He_{v+k}) \end{cases} \tag{35}$$

and the numerical characters of the appraisal clouds, as shown in Table 1, can be obtained using the 3σ rule and the golden segmentation [37].

Step 3: Determine the fuzzy membership functions.

In principle, we can have complex membership functions. However, the simplest membership functions, such as the triangular or trapezoid type, are the most efficient in many engineering applications [38], [39]. For each possible sequence of a single evaluation factor, we can find the maximum degree of membership to an appraisal grade j, which is the value in the sequence that is the closest to the expectation Ex_{vj} of the appraisal grade cloud C_{vj}; therefore, we adopted the triangle membership function to calculate the degree of membership within appraisal grades 1 to m [40], [41]. The functions and diagrams are shown in Table 2 and Fig. 4, respectively.

Step 4: Set the fuzzy mapping matrix.

The function of the fuzzy mapping matrix $\boldsymbol{R}$ can provide a fuzzy mapping from $\boldsymbol{U}$ to $\boldsymbol{V}_C$ via the corresponding membership function, which is shown in (36).

$$f : \boldsymbol{U} \to F(\boldsymbol{V}_C)u_i \mapsto \boldsymbol{R}_i(r_{i1}, r_{i2}, \cdots, r_{im}) \tag{36}$$

where $\boldsymbol{R}_i$ is the single factor appraisal vector, and F is a fuzzy mapping from u_i to the appraisal grades $\boldsymbol{V}_C$. Therefore, the fuzzy mapping matrix R is shown as

$$\boldsymbol{R} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m} \\ r_{21} & r_{22} & \cdots & r_{1m} \\ \vdots & \vdots & \cdots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nm} \end{bmatrix} \tag{37}$$

TABLE 2. Triangle membership function and health status.

Appraisal grades	Membership function
1	$\mu(x)=\begin{cases}\dfrac{x-Ex_{v2}}{Ex_{v1}-Ex_{v2}} & Ex_{v1}\le x<Ex_{v2}\\ 0 & Ex_{v2}\le x\end{cases}$
2	$\mu(x)=\begin{cases}\dfrac{x-Ex_{v1}}{Ex_{v2}-Ex_{v1}} & Ex_{v1}\le x<Ex_{v2}\\ \dfrac{x-Ex_{v3}}{Ex_{v2}-Ex_{v3}} & Ex_{v2}\le x<Ex_{v3}\\ 0 & Ex_{v3}\le x\end{cases}$
…	…
m–1	$\mu(x)=\begin{cases}0 & x<Ex_{vm-2}\\ \dfrac{x-Ex_{vm-2}}{Ex_{vm-1}-Ex_{vm-2}} & Ex_{vm-2}\le x<Ex_{vm-1}\\ \dfrac{x-Ex_{vm}}{Ex_{vm-1}-Ex_{vm}} & Ex_{vm-1}\le x<Ex_{vm}\end{cases}$
m	$\mu(x)=\begin{cases}0 & x<Ex_{vm-1}\\ \dfrac{x-Ex_{vm-1}}{Ex_{vm}-Ex_{vm-1}} & Ex_{vm-1}\le x\le Ex_{vm}\end{cases}$

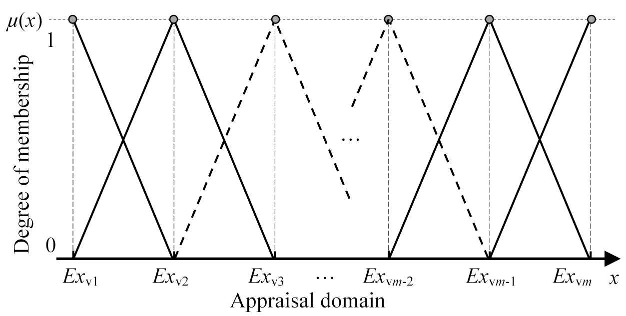

FIGURE 4. Triangle membership function diagrams.

Step 5: Get the cloud weight vector.

Based on the weight cloud calculation above, the cloud weight vector $\boldsymbol{W}=(C_{\mathrm{w}1}, C_{\mathrm{w}2}, \ldots, C_{\mathrm{w}n})$ corresponding to each evaluation factor can be obtained.

Step 6: Get the cloud appraisal vector.

Let the cloud appraisal vector $\boldsymbol{B}$ be

$$\boldsymbol{B}=(C_{\mathrm{B}1}, C_{\mathrm{B}2}, \ldots, C_{\mathrm{B}m}) \quad \boldsymbol{B}\in F(V) \tag{38}$$

where

$$C_{\mathrm{B}i}=C_{\mathrm{B}i}(Ex_{\mathrm{B}i}, En_{\mathrm{B}i}, He_{\mathrm{B}i}), \quad i=0,1,\cdots,m \tag{39}$$

By taking into account the importance of each factor, the single factor appraisal vector $\boldsymbol{R}_i$ should be given a corresponding cloud weight $C_{\mathrm{w}i}$, as shown in (40), to get the cloud appraisal vector $\boldsymbol{B}$.

$$\boldsymbol{B}=\boldsymbol{W}\circ\boldsymbol{R}=(C_{\mathrm{w}1}, C_{\mathrm{w}2}, \ldots, C_{\mathrm{w}n})\circ\boldsymbol{R} \tag{40}$$

Referring to (38) and (40), $\boldsymbol{B}$ can be further expressed as

$$\begin{bmatrix} C_{\mathrm{B}1}(Ex_{\mathrm{B}1}, En_{\mathrm{B}1}, He_{\mathrm{B}1})\\ C_{\mathrm{B}2}(Ex_{\mathrm{B}2}, En_{\mathrm{B}2}, He_{\mathrm{B}2})\\ \cdots\\ C_{\mathrm{B}m}(Ex_{\mathrm{B}m}, En_{\mathrm{B}m}, He_{\mathrm{B}m})\end{bmatrix}^T = \begin{bmatrix} C_{\mathrm{w}1}(Ex_{\mathrm{w}1}, En_{\mathrm{w}1}, He_{\mathrm{w}1})\\ C_{\mathrm{w}2}(Ex_{\mathrm{w}2}, En_{\mathrm{w}2}, He_{\mathrm{w}2})\\ \cdots\\ C_{\mathrm{w}n}(Ex_{\mathrm{w}n}, En_{\mathrm{w}n}, He_{\mathrm{w}n})\end{bmatrix}^T \circ \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1m}\\ r_{21} & r_{22} & \cdots & r_{1m}\\ \vdots & \vdots & \cdots & \vdots\\ r_{n1} & r_{n2} & \cdots & r_{nm}\end{bmatrix} \tag{41}$$

where $C_{\mathrm{B}i}$ can be calculated by the cloud arithmetic operations in (10) and (12), as shown in (42).

$$C_{\mathrm{B}i}(Ex_{\mathrm{B}i}, En_{\mathrm{B}i}, He_{\mathrm{B}i}) \Leftrightarrow \begin{cases} Ex_{\mathrm{B}i}=\sum_{j=1}^{n} r_{ji}Ex_{\mathrm{w}j}\\ En_{\mathrm{B}i}=\sqrt{\sum_{j=1}^{n} r_{ji}En_{\mathrm{w}j}^2}\\ He_{\mathrm{B}i}=\sqrt{\sum_{j=1}^{n} r_{ji}He_{\mathrm{w}j}^2}\end{cases} \tag{42}$$

Step 7: Get the evaluation result.

The cloud evaluation result E can be obtained by the cloud aggregation calculation with (43).

$$\begin{aligned} E &= C_{\mathrm{E}}(Ex_{\mathrm{E}}, En_{\mathrm{E}}, He_{\mathrm{E}})=\boldsymbol{B}\circ\boldsymbol{V}_{\mathrm{C}}^{\mathrm{T}}\\ &= \sum_{j=1}^{m}\left(C_{\mathrm{B}j}(Ex_{\mathrm{B}j}, En_{\mathrm{B}j}, He_{\mathrm{B}j})\cdot C_{\mathrm{v}j}(Ex_{\mathrm{v}j}, En_{\mathrm{v}j}, He_{\mathrm{v}j})\right)\end{aligned} \tag{43}$$

where

$$Ex_{\mathrm{E}}=\sum_{j=1}^{m} Ex_{\mathrm{v}j}Ex_{\mathrm{B}j} \tag{44}$$

$$En_{\mathrm{E}}=\sqrt{\sum_{j=1}^{m}\left((Ex_{\mathrm{v}j}Ex_{\mathrm{B}j})^2\left(\left(\frac{En_{\mathrm{v}j}}{Ex_{\mathrm{v}j}}\right)^2+\left(\frac{En_{\mathrm{B}j}}{Ex_{\mathrm{B}j}}\right)^2\right)\right)} \tag{45}$$

$$He_{\mathrm{E}}=\sqrt{\sum_{j=1}^{m}\left((Ex_{\mathrm{v}j}Ex_{\mathrm{B}j})^2\left(\left(\frac{He_{\mathrm{v}j}}{Ex_{\mathrm{v}j}}\right)^2+\left(\frac{He_{\mathrm{B}j}}{Ex_{\mathrm{B}j}}\right)^2\right)\right)} \tag{46}$$

By using (19) with the cloud aggregation result E and all appraisal grades, the qualitative evaluation analysis can be completed.

III. METHODOLOGY APPLICATION

To verify the proposed method, the evaluation item of an "Emergency Power Plant Start" was selected as an example to verify the application, and the results were analyzed.

The evaluation factors of the example evaluation items are shown in the second column of Table 3, and the original

TABLE 3. Evaluation factors and judgment weight clouds.

ID	Evaluation factor	Judgment cloud
I01	Engine room ventilation	$C_{P1}(0.83, 0.61, 0.19)$
I02	Power supply of local control box	$C_{P2}(8, 0.32, 0.42)$
I03	DO tank level	$C_{P3}(4.5, 0.83, 0.52)$
I04	LO sump level	$C_{P4}(3.6, 0.92, 0.35)$
I05	Cooling water tank level	$C_{P5}(2.8, 0.76, 0.23)$
I06	Start battery voltage	$C_{P6}(3.2, 0.45, 0.34)$
I07	Emergency generator speed	$C_{P7}(6, 0.25, 0.43)$
I08	DO inlet pressure	$C_{P8}(3.5, 0.38, 0.56)$
I09	LO inlet pressure	$C_{P9}(4.1, 0.24, 0.65)$
I10	Cylinder water outlet temperature	$C_{P10}(4.5, 0.56, 0.37)$
I11	Prime mover control mode	$C_{P11}(3, 0.66, 0.43)$
I12	Emergency generator voltage	$C_{P12}(7.2, 0.13, 0.53)$
I13	Emergency generator frequency	$C_{P13}(7.8, 0.21, 0.51)$
I14	Circuit breaker status	$C_{P14}(9.5, 0.72, 0.35)$
I15	Emergency lighting power supply	$C_{P15}(5.5, 0.69, 0.57)$
I16	Other loads power supply	$C_{P16}(6.3, 0.72, 0.48)$
I17	Generator control mode	$C_{P17}(2, 0.68, 0.35)$
I18	Tie switch control mode	$C_{P18}(1.8, 0.73, 0.46)$

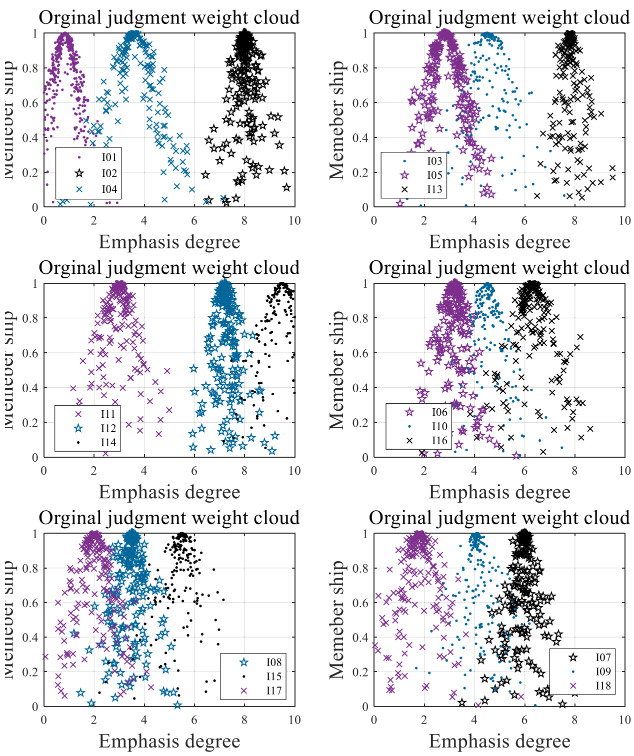

FIGURE 5. Visual distribution of the judgment weight clouds.

judgment weight clouds according to the factors generated by the BCG with the data collected via the Delphi method are shown in the third column of Table 3. The visual distribution of the judgment weight clouds are shown in Fig. 5.

A. CLOUD WEIGHT VECTOR CALCULATION

Via (24) and (25), the judgment cloud matrix $\boldsymbol{A}$ of the comparison result can be calculated in the form of three numerical character matrixes as shown at the next page.

The cloud weight vector $\boldsymbol{W}$ can be calculated with the judgment cloud matrix $\boldsymbol{A}$ via (28) and (29):

$$
\begin{aligned}
\boldsymbol{W} &= (C_{w1}, C_{w1}, \ldots, C_{w18},) \\
C_{w1} &= C_{w1}(0.010, 0.007, 0.0025), \\
C_{w2} &= C_{w2}(0.095, 0.025, 0.0137) \\
C_{w3} &= C_{w3}(0.053, 0.017, 0.0093) \\
C_{w4} &= C_{w4}(0.043, 0.015, 0.0070) \\
C_{w5} &= C_{w5}(0.033, 0.012, 0.0052) \\
C_{w6} &= C_{w6}(0.038, 0.011, 0.0064) \\
C_{w7} &= C_{w7}(0.071, 0.019, 0.0108) \\
C_{w8} &= C_{w8}(0.042, 0.012, 0.0084) \\
C_{w9} &= C_{w9}(0.049, 0.013, 0.0098) \\
C_{w10} &= C_{w10}(0.053, 0.015, 0.0083) \\
C_{w11} &= C_{w11}(0.036, 0.011, 0.0068) \\
C_{w12} &= C_{w12}(0.086, 0.022, 0.0130) \\
C_{w13} &= C_{w13}(0.093, 0.024, 0.0138) \\
C_{w14} &= C_{w14}(0.113, 0.030, 0.0158) \\
C_{w15} &= C_{w15}(0.065, 0.019, 0.0109) \\
C_{w16} &= C_{w16}(0.075, 0.021, 0.0115) \\
C_{w17} &= C_{w17}(0.024, 0.010, 0.0051) \\
C_{w18} &= C_{w18}(0.021, 0.010, 0.0059)
\end{aligned}
$$

The visual distribution of cloud weights C_{w1} to C_{w18} are shown in Fig. 6.

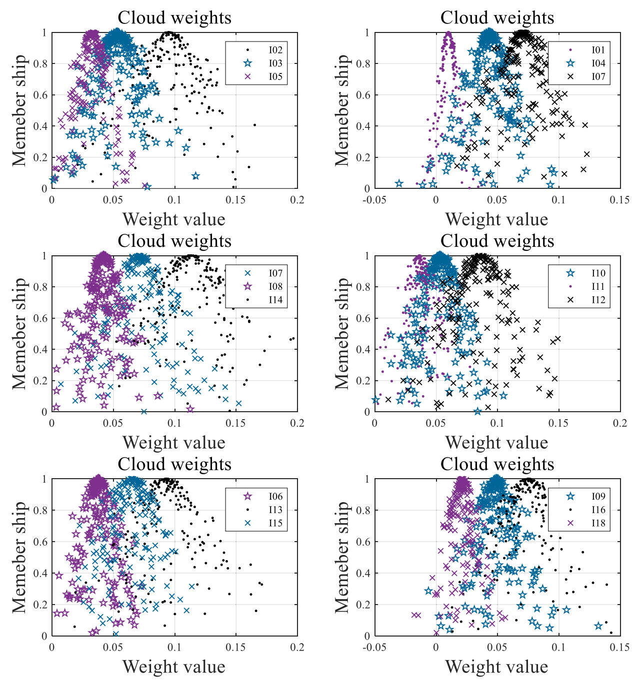

FIGURE 6. Visual distribution of the cloud weights.

$$
\boldsymbol{A}(Ex) = \begin{bmatrix}
1.00 & 0.11 & 0.19 & 0.23 & 0.30 & 0.26 & 0.14 & 0.24 & 0.20 & 0.19 & 0.28 & 0.12 & 0.11 & 0.09 & 0.15 & 0.13 & 0.42 & 0.47 \\
9.52 & 1.00 & 1.78 & 2.22 & 2.86 & 2.50 & 1.33 & 2.29 & 1.95 & 1.78 & 2.67 & 1.11 & 1.03 & 0.84 & 1.45 & 1.27 & 4.00 & 4.44 \\
5.36 & 0.56 & 1.00 & 1.25 & 1.61 & 1.41 & 0.75 & 1.29 & 1.10 & 1.00 & 1.50 & 0.63 & 0.58 & 0.47 & 0.82 & 0.71 & 2.25 & 2.50 \\
4.29 & 0.45 & 0.80 & 1.00 & 1.29 & 1.13 & 0.60 & 1.03 & 0.88 & 0.80 & 1.20 & 0.50 & 0.46 & 0.38 & 0.65 & 0.57 & 1.80 & 2.00 \\
3.33 & 0.35 & 0.62 & 0.78 & 1.00 & 0.88 & 0.47 & 0.80 & 0.68 & 0.62 & 0.93 & 0.39 & 0.36 & 0.29 & 0.51 & 0.44 & 1.40 & 1.56 \\
3.81 & 0.40 & 0.71 & 0.89 & 1.14 & 1.00 & 0.53 & 0.91 & 0.78 & 0.71 & 1.07 & 0.44 & 0.41 & 0.34 & 0.58 & 0.51 & 1.60 & 1.78 \\
7.14 & 0.75 & 1.33 & 1.67 & 2.14 & 1.88 & 1.00 & 1.71 & 1.46 & 1.33 & 2.00 & 0.83 & 0.77 & 0.63 & 1.09 & 0.95 & 3.00 & 3.33 \\
4.17 & 0.44 & 0.78 & 0.97 & 1.25 & 1.09 & 0.58 & 1.00 & 0.85 & 0.78 & 1.17 & 0.49 & 0.45 & 0.37 & 0.64 & 0.56 & 1.75 & 1.94 \\
4.88 & 0.51 & 0.91 & 1.14 & 1.46 & 1.28 & 0.68 & 1.17 & 1.00 & 0.91 & 1.37 & 0.57 & 0.53 & 0.43 & 0.75 & 0.65 & 2.05 & 2.28 \\
5.36 & 0.56 & 1.00 & 1.25 & 1.61 & 1.41 & 0.75 & 1.29 & 1.10 & 1.00 & 1.50 & 0.63 & 0.58 & 0.47 & 0.82 & 0.71 & 2.25 & 2.50 \\
3.57 & 0.38 & 0.67 & 0.83 & 1.07 & 0.94 & 0.50 & 0.86 & 0.73 & 0.67 & 1.00 & 0.42 & 0.38 & 0.32 & 0.55 & 0.48 & 1.50 & 1.67 \\
8.57 & 0.90 & 1.60 & 2.00 & 2.57 & 2.25 & 1.20 & 2.06 & 1.76 & 1.60 & 2.40 & 1.00 & 0.92 & 0.76 & 1.31 & 1.14 & 3.60 & 4.00 \\
9.29 & 0.98 & 1.73 & 2.17 & 2.79 & 2.44 & 1.30 & 2.23 & 1.90 & 1.73 & 2.60 & 1.08 & 1.00 & 0.82 & 1.42 & 1.24 & 3.90 & 4.33 \\
11.31 & 1.19 & 2.11 & 2.64 & 3.39 & 2.97 & 1.58 & 2.71 & 2.32 & 2.11 & 3.17 & 1.32 & 1.22 & 1.00 & 1.73 & 1.51 & 4.75 & 5.28 \\
6.55 & 0.69 & 1.22 & 1.53 & 1.96 & 1.72 & 0.92 & 1.57 & 1.34 & 1.22 & 1.83 & 0.76 & 0.71 & 0.58 & 1.00 & 0.87 & 2.75 & 3.06 \\
7.50 & 0.79 & 1.40 & 1.75 & 2.25 & 1.97 & 1.05 & 1.80 & 1.54 & 1.40 & 2.10 & 0.88 & 0.81 & 0.66 & 1.15 & 1.00 & 3.15 & 3.50 \\
2.38 & 0.25 & 0.44 & 0.56 & 0.71 & 0.63 & 0.33 & 0.57 & 0.49 & 0.44 & 0.67 & 0.28 & 0.26 & 0.21 & 0.36 & 0.32 & 1.00 & 1.11 \\
2.14 & 0.23 & 0.40 & 0.50 & 0.64 & 0.56 & 0.30 & 0.51 & 0.44 & 0.40 & 0.60 & 0.25 & 0.23 & 0.19 & 0.33 & 0.29 & 0.90 & 1.00
\end{bmatrix}
$$

$$
\boldsymbol{A}(En) = \begin{bmatrix}
0.00 & 0.08 & 0.14 & 0.18 & 0.23 & 0.19 & 0.10 & 0.18 & 0.15 & 0.14 & 0.21 & 0.08 & 0.08 & 0.06 & 0.11 & 0.10 & 0.34 & 0.39 \\
6.93 & 0.00 & 0.34 & 0.57 & 0.78 & 0.37 & 0.08 & 0.26 & 0.14 & 0.23 & 0.60 & 0.05 & 0.05 & 0.07 & 0.19 & 0.15 & 1.37 & 1.81 \\
4.01 & 0.11 & 0.00 & 0.39 & 0.53 & 0.33 & 0.14 & 0.28 & 0.21 & 0.22 & 0.43 & 0.12 & 0.11 & 0.09 & 0.18 & 0.15 & 0.87 & 1.11 \\
3.30 & 0.12 & 0.25 & 0.00 & 0.48 & 0.33 & 0.16 & 0.29 & 0.23 & 0.23 & 0.40 & 0.13 & 0.12 & 0.10 & 0.19 & 0.16 & 0.77 & 0.96 \\
2.58 & 0.10 & 0.20 & 0.29 & 0.00 & 0.27 & 0.13 & 0.23 & 0.19 & 0.19 & 0.33 & 0.11 & 0.10 & 0.08 & 0.15 & 0.13 & 0.61 & 0.76 \\
2.82 & 0.06 & 0.16 & 0.26 & 0.35 & 0.00 & 0.08 & 0.16 & 0.12 & 0.13 & 0.28 & 0.06 & 0.06 & 0.05 & 0.11 & 0.09 & 0.59 & 0.76 \\
5.20 & 0.04 & 0.25 & 0.43 & 0.59 & 0.28 & 0.00 & 0.20 & 0.11 & 0.17 & 0.45 & 0.04 & 0.04 & 0.05 & 0.14 & 0.12 & 1.03 & 1.36 \\
3.06 & 0.05 & 0.17 & 0.27 & 0.37 & 0.19 & 0.07 & 0.00 & 0.11 & 0.13 & 0.29 & 0.05 & 0.05 & 0.05 & 0.11 & 0.09 & 0.62 & 0.82 \\
3.56 & 0.04 & 0.18 & 0.30 & 0.41 & 0.20 & 0.05 & 0.14 & 0.00 & 0.13 & 0.31 & 0.03 & 0.03 & 0.04 & 0.10 & 0.08 & 0.71 & 0.93 \\
3.95 & 0.07 & 0.22 & 0.36 & 0.48 & 0.26 & 0.10 & 0.21 & 0.15 & 0.00 & 0.38 & 0.08 & 0.07 & 0.07 & 0.14 & 0.12 & 0.81 & 1.06 \\
2.71 & 0.08 & 0.19 & 0.28 & 0.37 & 0.24 & 0.11 & 0.21 & 0.17 & 0.17 & 0.00 & 0.09 & 0.09 & 0.07 & 0.14 & 0.12 & 0.61 & 0.77 \\
6.23 & 0.04 & 0.30 & 0.51 & 0.70 & 0.32 & 0.05 & 0.23 & 0.11 & 0.20 & 0.53 & 0.00 & 0.03 & 0.06 & 0.17 & 0.13 & 1.23 & 1.62 \\
6.75 & 0.05 & 0.32 & 0.56 & 0.76 & 0.35 & 0.06 & 0.25 & 0.12 & 0.22 & 0.58 & 0.04 & 0.00 & 0.07 & 0.18 & 0.15 & 1.33 & 1.76 \\
8.26 & 0.10 & 0.42 & 0.70 & 0.96 & 0.47 & 0.14 & 0.36 & 0.22 & 0.31 & 0.74 & 0.10 & 0.10 & 0.00 & 0.25 & 0.21 & 1.65 & 2.18 \\
4.83 & 0.09 & 0.27 & 0.43 & 0.59 & 0.32 & 0.12 & 0.26 & 0.19 & 0.22 & 0.46 & 0.10 & 0.09 & 0.08 & 0.00 & 0.15 & 1.00 & 1.30 \\
5.51 & 0.10 & 0.30 & 0.49 & 0.66 & 0.36 & 0.13 & 0.28 & 0.20 & 0.24 & 0.52 & 0.10 & 0.09 & 0.09 & 0.19 & 0.00 & 1.13 & 1.47 \\
1.91 & 0.09 & 0.17 & 0.24 & 0.31 & 0.23 & 0.11 & 0.20 & 0.17 & 0.16 & 0.27 & 0.09 & 0.09 & 0.07 & 0.13 & 0.11 & 0.00 & 0.59 \\
1.78 & 0.09 & 0.18 & 0.24 & 0.31 & 0.24 & 0.12 & 0.22 & 0.18 & 0.17 & 0.28 & 0.10 & 0.09 & 0.08 & 0.14 & 0.12 & 0.48 & 0.00
\end{bmatrix}
$$

$$
\boldsymbol{A}(He) = \begin{bmatrix}
0.00 & 0.02 & 0.05 & 0.06 & 0.07 & 0.07 & 0.03 & 0.07 & 0.06 & 0.04 & 0.07 & 0.03 & 0.03 & 0.02 & 0.04 & 0.03 & 0.12 & 0.16 \\
2.21 & 0.00 & 0.23 & 0.25 & 0.28 & 0.30 & 0.12 & 0.38 & 0.33 & 0.17 & 0.41 & 0.10 & 0.09 & 0.05 & 0.17 & 0.12 & 0.73 & 1.16 \\
1.36 & 0.07 & 0.00 & 0.19 & 0.23 & 0.22 & 0.10 & 0.25 & 0.22 & 0.14 & 0.28 & 0.09 & 0.08 & 0.06 & 0.13 & 0.10 & 0.47 & 0.70 \\
1.06 & 0.05 & 0.12 & 0.00 & 0.16 & 0.16 & 0.07 & 0.19 & 0.16 & 0.10 & 0.21 & 0.06 & 0.05 & 0.04 & 0.09 & 0.07 & 0.36 & 0.55 \\
0.80 & 0.03 & 0.09 & 0.10 & 0.00 & 0.12 & 0.05 & 0.14 & 0.12 & 0.07 & 0.15 & 0.04 & 0.04 & 0.03 & 0.07 & 0.05 & 0.27 & 0.42 \\
0.95 & 0.05 & 0.11 & 0.13 & 0.15 & 0.00 & 0.07 & 0.18 & 0.15 & 0.10 & 0.19 & 0.06 & 0.05 & 0.04 & 0.09 & 0.07 & 0.33 & 0.49 \\
1.69 & 0.07 & 0.18 & 0.20 & 0.23 & 0.24 & 0.00 & 0.30 & 0.25 & 0.15 & 0.32 & 0.09 & 0.07 & 0.05 & 0.14 & 0.10 & 0.57 & 0.88 \\
1.15 & 0.07 & 0.15 & 0.18 & 0.22 & 0.21 & 0.10 & 0.00 & 0.19 & 0.14 & 0.25 & 0.09 & 0.08 & 0.06 & 0.12 & 0.10 & 0.41 & 0.59 \\
1.35 & 0.09 & 0.18 & 0.21 & 0.26 & 0.24 & 0.12 & 0.26 & 0.00 & 0.16 & 0.29 & 0.10 & 0.09 & 0.07 & 0.14 & 0.11 & 0.48 & 0.69 \\
1.29 & 0.05 & 0.14 & 0.16 & 0.19 & 0.19 & 0.08 & 0.23 & 0.20 & 0.00 & 0.25 & 0.07 & 0.06 & 0.04 & 0.11 & 0.08 & 0.44 & 0.67 \\
0.96 & 0.06 & 0.12 & 0.14 & 0.18 & 0.17 & 0.08 & 0.18 & 0.16 & 0.11 & 0.00 & 0.07 & 0.06 & 0.05 & 0.10 & 0.08 & 0.34 & 0.49 \\
2.04 & 0.08 & 0.22 & 0.24 & 0.28 & 0.29 & 0.12 & 0.36 & 0.31 & 0.18 & 0.39 & 0.00 & 0.09 & 0.06 & 0.17 & 0.12 & 0.68 & 1.06 \\
2.19 & 0.08 & 0.23 & 0.25 & 0.29 & 0.30 & 0.13 & 0.39 & 0.33 & 0.18 & 0.41 & 0.11 & 0.00 & 0.06 & 0.17 & 0.12 & 0.73 & 1.14 \\
2.59 & 0.08 & 0.26 & 0.27 & 0.31 & 0.33 & 0.13 & 0.45 & 0.38 & 0.19 & 0.47 & 0.11 & 0.09 & 0.00 & 0.19 & 0.13 & 0.85 & 1.36 \\
1.63 & 0.08 & 0.19 & 0.22 & 0.26 & 0.26 & 0.12 & 0.30 & 0.25 & 0.16 & 0.32 & 0.10 & 0.09 & 0.06 & 0.00 & 0.11 & 0.56 & 0.84 \\
1.79 & 0.07 & 0.19 & 0.22 & 0.25 & 0.26 & 0.11 & 0.32 & 0.27 & 0.16 & 0.34 & 0.09 & 0.08 & 0.06 & 0.15 & 0.00 & 0.60 & 0.93 \\
0.68 & 0.05 & 0.09 & 0.11 & 0.14 & 0.13 & 0.06 & 0.14 & 0.12 & 0.09 & 0.15 & 0.05 & 0.05 & 0.04 & 0.07 & 0.06 & 0.00 & 0.34 \\
0.73 & 0.06 & 0.11 & 0.14 & 0.17 & 0.16 & 0.08 & 0.16 & 0.13 & 0.11 & 0.18 & 0.07 & 0.06 & 0.05 & 0.09 & 0.08 & 0.28 & 0.00
\end{bmatrix}
$$

B. APPRAISAL GRADE CLOUDS GENERATION

Set the appraisal domain $[x_{\min}, x_{\max}]$ as [0, 100]; and set the appraisal grade m as 7 with grade 1 to grade 7, which mean "None, Very Low, Low, Medium, High, Very High, and Perfect", respectively [42]. Therefore, according to (31), the cloud set of appraisal grade $\boldsymbol{V}_\mathrm{C}$ can be described as

$$\boldsymbol{V}_\mathrm{C} = \{C_{v1}, C_{v2}, C_{v3}, C_{v4}, C_{v5}, C_{v6}, C_{v7}\}$$
$$C_{vj} = C_{vj}(Ex_{vj}, En_{vj}, He_{vj}), \quad j = 0, 1, \ldots, 7$$

and the numerical characters of the appraisal grade clouds can be calculated by referring to Table 1:

$$\begin{aligned} C_{v1} &= C_{v1}(0, 8.99, 1.49) \\ C_{v2} &= C_{v2}(16.68, 5.56, 2.78) \\ C_{v3} &= C_{v3}(37.27, 3.43, 1.72) \\ C_{v4} &= C_{v4}(50, 2.12, 1.06) \\ C_{v5} &= C_{v5}(62.73, 3.43, 1.72) \\ C_{v6} &= C_{v6}(83.32, 5.26, 2.78) \\ C_{v7} &= C_{v7}(100, 8.99, 4.49) \end{aligned}$$

Therefore, the expectation vector of appraisal grade $\boldsymbol{V}_\mathrm{C}(Ex)$ is

$$\boldsymbol{V}_\mathrm{C}(Ex) = (0, 16.68, 37.27, 50, 62.73, 83.32, 100)$$

The appraisal grade clouds with the calculated numerical characters, which will give an appraisal grade standard for comparisons in the assessment process, are shown in Fig. 7.

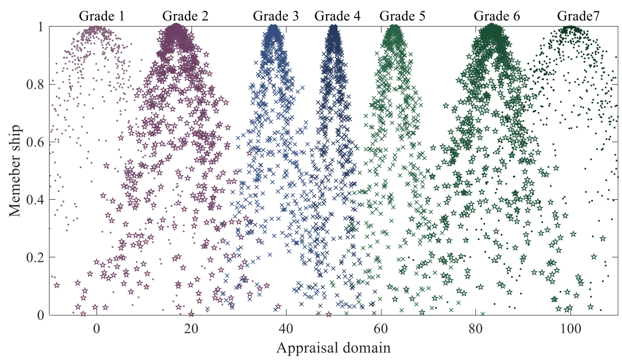

FIGURE 7. Visual distribution of the appraisal grade clouds.

C. CLOUD APPRAISAL VECTOR CALCULATION

Before getting the cloud appraisal vector, the parameter standardization and domain conversion should be finished. The defined conversion function can give a mapping from the application domain to the appraisal domain, as shown in Fig. 8. The specific parameter standard, the selected conversion function type and the actual converted value for each evaluation factor are shown in Table 4.

Based on the actual converted value (as shown in the fourth column of Table 4) with the domain conversion functions, the fuzzy mapping matrix $\boldsymbol{R}$ can be obtained by (36) and (37) associated with the triangle membership functions in Table 2 by inserting the actual parameter value of m and $Ex_{v1}, Ex_{v2}, \ldots, Ex_{v7}$.

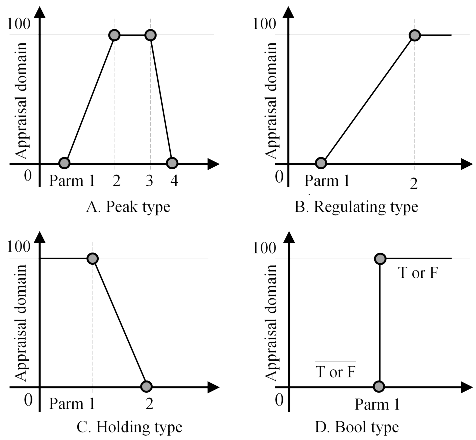

FIGURE 8. Domain conversion function types.

TABLE 4. Parameter standards and membership types.

ID	Standard statu/value	Mapping type	Mapping value
I01	–40 mmWC to 0 mmWC	A	85.9
I02	True	D	100
I03	20% to 95 %	A	96.7
I04	40% to 95 %	A	75.2
I05	Above 50 %	B	58.3
I06	Above 20 V	B	80.6
I07	Less than 1800 rpm	C	100
I08	Above 0.6 bar	B	95.9
I09	Above 1.4 bar	B	84.1
I10	Less than 90 °C	C	46.5
I11	True	D	0
I12	440V，±1 %	A	100
I13	60HZ，±10 %	A	66.5
I14	True	D	100
I15	True	D	100
I16	More than 7	B	32.6
I17	True	D	0
I18	True	D	100

$$\boldsymbol{R} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0.84 & 0.16 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0.2 & 0.8 \\ 0 & 0 & 0 & 0 & 0.39 & 0.61 & 0 \\ 0 & 0 & 0 & 0.35 & 0.65 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0.13 & 0.87 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0.25 & 0.75 \\ 0 & 0 & 0 & 0 & 0 & 0.95 & 0.05 \\ 0 & 0 & 0.27 & 0.73 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0.82 & 0.18 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0.23 & 0.77 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

D. CLOUD EVALUATION RESULT AGGREGATION

The cloud result E of the fuzzy comprehensive evaluation can be obtained by inserting $\boldsymbol{B}$ and $\boldsymbol{V}_\mathrm{C}$ into the cloud aggregation equations from (43) to (46).

$$E = (78.5908, 7.9954, 4.3298)$$

Using (19) to compare cloud E in order with the appraisal grade clouds $\boldsymbol{V}_\mathrm{C}$, the following similarity vector can be obtained.

$$\boldsymbol{S} = (0, 0, 0, 0.0284, 0.3505, 0.6624, 0.3887)$$

Via the FCG method, the aggregation cloud E can be visually compared with standard appraisal grade clouds, as shown in Fig. 9; and via (5) with $k = 0$, the expectation curves can be generated, as shown in Fig. 10.

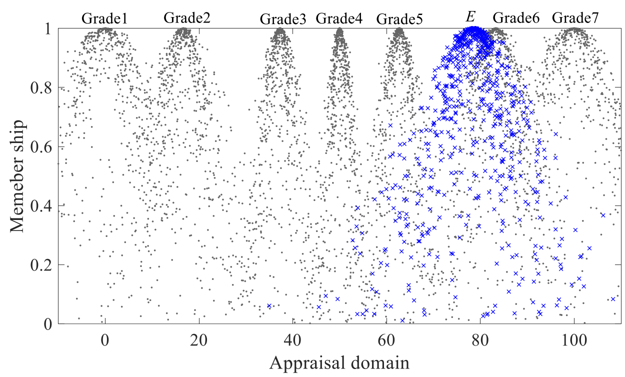

FIGURE 9. The evaluation result cloud in the appraisal grade clouds.

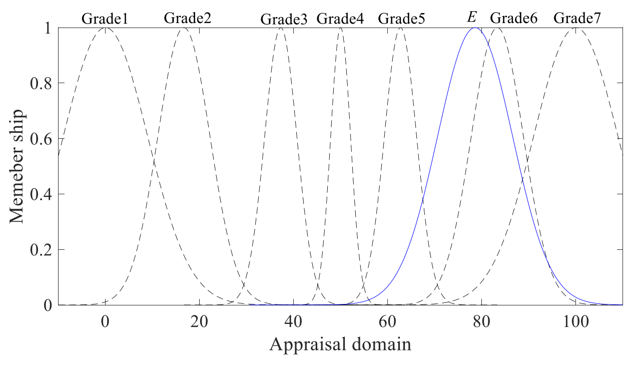

FIGURE 10. The expectation curves of the clouds in Fig. 9.

E. TWO ADDITIONAL COMPARATIVE EXAMPLES

To further verify the effectiveness of the method through comparative analysis, the evaluation results of two additional examples are given based on the same proposed method.

1) AN EXAMPLE WITH DIFFERENT OPERATIONS

This example has the same cloud weights as the first example, but some evaluation factors have changed due to operational differences, which are shown in Table 5.

TABLE 5. Differences in the mapping values compared with example 1.

ID	Standard statu/value	Example 1	This example
I03	20 % to 95 %	96.7	**28.4**
I04	40 % to 95 %	75.2	**35.5**
I05	Above 50 %	58.3	**11.2**
I14	True	100	**0**
I16	More than 7	32.6	**14.3**

Using the same calculation method, the evaluation cloud result E_O and the similarity vector $\boldsymbol{S}_\mathrm{O}$ are calculated as follows:

$$E_\mathrm{O} = (59.0147, 6.4679, 3.5984)$$
$$\boldsymbol{S}_\mathrm{O} = (0, 0, 0.1450, 0.3070, 0.4976, 0.1827, 0.0577)$$

The visual comparisons of cloud E_O with E in the standard appraisal grade clouds are shown in Fig. 11 and Fig. 12.

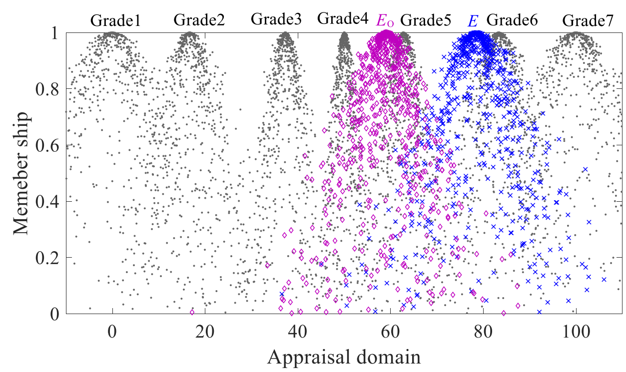

FIGURE 11. The evaluation result clouds in the appraisal grade clouds.

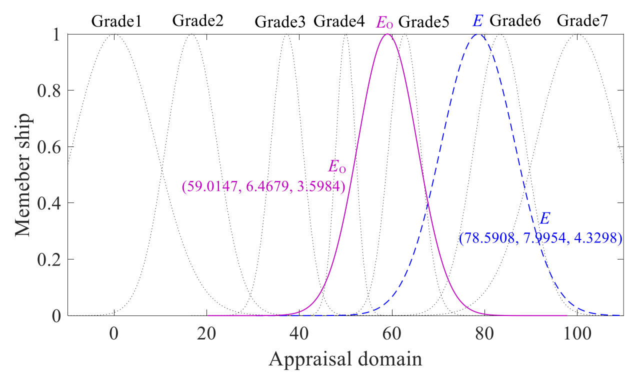

FIGURE 12. The expectation curves of the clouds in Fig. 11.

2) AN EXAMPLE WITH DIFFERENT CLOUD WEIGHTS

This example has the same operations in the ERS as the first example, but due to the modification (as shown in Table 6) of some judgment weight clouds in Table 3, the weight cloud of each evaluation factor has also changed. The differences in the cloud weights are shown in Table 7.

TABLE 6. The modified judgment weights compared with example 1.

ID	Example 1	This example
I02	(8, 0.32, 0.42)	**(4.1, 0.45, 0.35)**
I7	(6, 0.25, 0.43)	**(2.1, 0.33, 0.44)**
I9	(4.1, 0.24, 0.65)	**(8.8, 0.17, 0.71)**
I17	(2, 0.68, 0.35)	**(6.8, 0.63, 0.41)**

TABLE 7. Differences in the cloud weights compared with example 1.

ID	Example 1	This example
I01	(0.010, 0.007, 0.0025)	(0.010, 0.007, 0.0025)
I02	(0.095, 0.025, 0.0137)	**(0.048, 0.013, 0.0075)**
I03	(0.053, 0.017, 0.0093)	**(0.052, 0.016, 0.0091)**
I4	(0.043, 0.015, 0.0070)	(**0.042**, 0.015, **0.0068**)
I5	(0.033, 0.012, 0.0052)	(0.033, 0.012, **0.0051**)
I6	(0.038, 0.011, 0.0064)	(0.038, **0.010**, **0.0063**)
I7	(0.071, 0.019, 0.0108)	**(0.025, 0.007, 0.0059)**
I8	(0.042, 0.012, 0.0084)	**(0.041, 0.011, 0.0083)**
I9	(0.049, 0.013, 0.0098)	**(0.103, 0.026, 0.0159)**
I10	(0.053, 0.015, 0.0083)	(0.052, 0.015, **0.0082**)
I11	(0.036, 0.011, 0.0068)	(**0.035**, 0.011, **0.0067**)
I12	(0.086, 0.022, 0.0130)	**(0.084, 0.021, 0.0127)**
I13	(0.093, 0.024, 0.0138)	**(0.091, 0.023, 0.0135)**
I14	(0.113, 0.030, 0.0158)	**(0.111, 0.029, 0.0154)**
I15	(0.065, 0.019, 0.0109)	**(0.064, 0.018, 0.0107)**
I16	(0.075, 0.021, 0.0115)	**(0.073, 0.020, 0.0112)**
I17	(0.024, 0.010, 0.0051)	**(0.079, 0.021, 0.0116)**
I18	(0.021, 0.010, 0.0059)	(0.021, 0.010, **0.0058**)

Based on the same calculation method, the evaluation cloud result E_W and the similarity vector S_W are calculated as follows:

$$E_W = (72.5553, 7.1281, 3.6950)$$
$$S_W = (0, 0, 0, 0.0966, 0.4516, 0.5237, 0.2582)$$

The visual comparison of cloud E_W with E in the standard appraisal grade clouds are shown in Fig. 13 and Fig. 14.

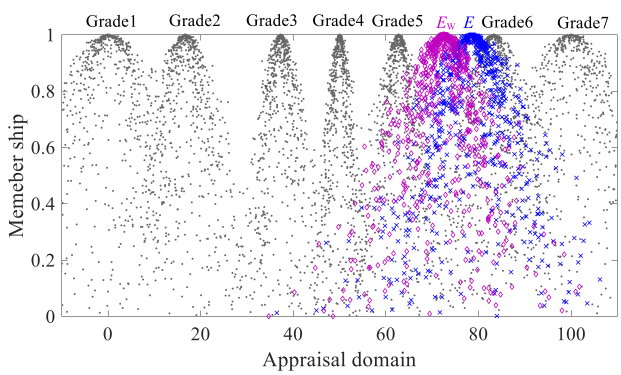

FIGURE 13. The evaluation result clouds in the appraisal grade clouds.

F. RESULTS AND COMPARATIVE ANALYSIS

For a cloud evaluation result $C(Ex, En, He)$ and the similarity vector S, Ex is the quantitative evaluation result related to task completion, which similar to the traditional assessment

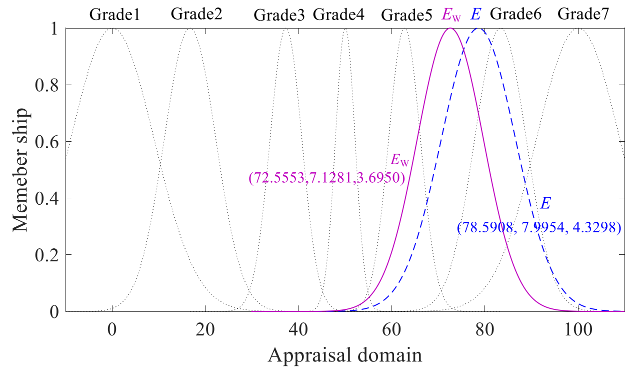

FIGURE 14. The expectation curves of the clouds in Fig. 13.

result, but Ex is the expectation accompanied by a uncertainty index En and a randomness index He, both of which are the smaller, the better. If En and He are both 0, then the quantitative evaluation result Ex can be completely accepted. However, due to the existence of human subjectivity and the fuzziness of the appraisal grades, this situation will rarely happen. In addition, the quantitative vector $\boldsymbol{S}$ represents the similarities between the evaluation result and the divided appraisal grades, and we can use it to get a qualitative analysis result via the maximum similarity principle.

The comparison of the results for the above examples is shown in Table 8. The relevant analyses of the results are as follows:

TABLE 8. Evaluation results for the 3 examples.

	Example 1	Example 2	Example 3
Ex	78.5908	59.0147	72.5553
En	7.9954	6.4679	7.1281
He	4.3298	3.5984	3.6950
Grade	6/0.6624	5/0.4976	6/0.5237

i Example 1: The quantitative evaluation result is 78.5908, which is accompanied by an uncertainty index of 7.9954 and a randomness index of 4.3298, both of which are derived from the fuzziness of the cloud weights and the appraisal grades in the cloud aggregation calculation process. The qualitative evaluation result is grade 6/"Very High" according to the maximum similarity principle.

ii Example 2 compared to example 1: Since example 2 has the same cloud weights as Example 1, the changes in E_O and S_O compared with E and $\boldsymbol{S}$ are mainly caused by the different operations. Due to the decrease that occurred in the changed operation mapping values, as shown in Table 5, the expectation result Ex was reduced to 59.0147. In addition, because the similarity trended to grade 5, the uncertainty index and randomness index were lower. En and He decreased to 6.4679 and 3.5984.

iii Example 3 compared to example 1: Because example 3 and example 1 have the same operations in the ERS, the changes in E_W and $\boldsymbol{S}_W$ compared with E and $\boldsymbol{S}$ were mainly caused by the changed cloud weights. From Table 7, we can see that some expectations of cloud weighs have changed, and so the expectation of cloud result was also recalculated according to fuzzy logic. In addition, because the changed En and He in the cloud weights generally tend to decrease, the uncertainty index and randomness index of the evaluation result also decrease, and the fuzziness of the evaluation result decreases.

As the evaluation is submitted, the evaluation results of E and $\boldsymbol{S}$ will be further handed over to people for decision-making or to a third-party decision-making system for further auxiliary processing.

IV. CONCLUSION

In the maritime field, the development of the crew competence evaluation methods from manual judgment to machine automated and intelligent evaluation is an inevitable development trend. The research on intelligent assessment method in an ERS can effectively promote crew competency assessments. It can also provide technical and program support for the further implementation of new international conventions.

As a software function, the method proposed is embedded in the software of an ERS. During the running of the ERS, the evaluation function unit reads the user's operating information and calculates the evaluation result after the operation is completed. The main calculation load undertaken by the server is the simulation calculation of the large electromechanical systems of the engine room. The calculation costs of this method are relatively small and will not become a computational burden for the main thread.

In the next step, the methodology elaborated here can be further expanded as follows: combine the quantitative analysis of engine room team collaboration with fuzzy evaluation factors to evaluate team collaboration, introduce hesitant fuzzy elements in the cloud appraisal vector to enhance the integration of expert knowledge, and introduce the multi-hierarchical structure in the evaluation model for complex evaluation tasks and calculate the hierarchical weights to evaluate large-scale system operations.

NOMENCLATURE

$\boldsymbol{A}$ = judgment cloud matrix
$\boldsymbol{B}$ = cloud appraisal vector
C = qualitative concept in U
C_{Bi} = element i of cloud appraisal vector $\boldsymbol{B}$
C_{wi} = cloud weight corresponding to the vector $\boldsymbol{R}_i$
E = cloud evaluation result
En = entropy
$\hat{E}n$ = estimate of En
En_E = entropy of the cloud evaluation result
Ex = expectation value
$\hat{E}x$ = sample mean
Ex_E = expectation of the cloud evaluation result
Ex_{vi} = expectation of the cloud appraisal grade i
En_{vi} = entropy of the cloud appraisal grade i
He = hyperentropy
$\hat{H}e$ = estimate of He
He_E = hyperentropy of the cloud evaluation result
He_{vi} = hyperentropy of the cloud appraisal grade i
F = fuzzy mapping
i = cloud drop ID; or evaluation factor ID
j = appraisal grade ID
k = entropy expectation parameter; or temporary variables in appraisal grades
M = number of cloud drops in BCG
m = number of appraisal grades
N = number of cloud drops in FCG
n = number of evaluation factors
$\boldsymbol{P}$ = expert judgment set vector
$\boldsymbol{p}_i$ = expert judgment set for i evaluation factor
$\boldsymbol{R}$ = fuzzy mapping matrix
$\boldsymbol{R}_i$ = single factor appraisal vector
r_{ij} = element j of the single factor appraisal vector $\boldsymbol{R}_i$
$\boldsymbol{S}$ = similarity vector of clouds
S = similarity of two clouds
S_P = position similarity of two clouds
S_S = shape similarity of two clouds
x = value in quantitative domain
x_{min} = lower limit of the appraisal domain
x_{max} = upper limit of the appraisal domain
$\boldsymbol{U}$ = evaluation factors set
U = quantitative domain by accurate numbers
u_i = evaluation factor i
$\boldsymbol{V}_C$ = cloud set of appraisal grades
$\boldsymbol{W}$ = cloud weight vector
y = membership degree of x to C
σ = standard deviation

REFERENCES

[1] Y. Yang, C. Suo, W. Hao, and Z. Zhang, "Overview on intelligent comprehensive evaluation methods," *Rev. Comput. Eng. Stud.*, vol. 5, no. 4, pp. 59–64, Dec. 2018.
[2] S. Russell and P. Norvig, "Artificial intelligence," in *Artificial Intelligence: A Modern Approach*, 4th ed. Englewood Cliffs, NJ, USA: Prentice-Hall, 2020, pp. 1–36.
[3] H. S. Sii, J. Wang, T. Ruxton, J. B. Yang, and J. Liu, "Use of fuzzy logic approaches to safety assessment in maritime engineering applications," *J. Mar. Eng. Technol.*, vol. 3, no. 2, pp. 45–58, Jan. 2004.
[4] J. Ren, I. Jenkinson, H. S. Sii, J. Wang, L. Xu, and J. B. Yang, "An offshore safety assessment framework using fuzzy reasoning and evidential synthesis approaches," *J. Mar. Eng. Technol.*, vol. 4, no. 1, pp. 3–16, Jan. 2005.
[5] K. Ikenishi, T. Hikima, K. Sato, H. H. Tran, and T. C. Luu, "Study on maritime education and training method of engine room simulator based on PC," *J. Jpn. Inst. Mar. Eng.*, vol. 41, no. 2, pp. 285–290, 2006.
[6] P. Vasilakis and N. Nikitakos, "Technology achievements in maritime educational procedures: Behavioral assessment framework," *Int. J. Assessment Eval.*, vol. 20, no. 1, pp. 1–13, Aug. 2013.
[7] W. Nie, Y. Wu, D. Hu, and Y. Li, "Research of automatic scoring arithmetic for examination of engine room simulator," *J. Wuhan Univ. Technol., Transp. Sci. Eng.*, vol. 37, no. 4, pp. 834–838, Aug. 2013.
[8] H. Cao, Y. X. Ma, and B. Z. Jia, "An intelligent evaluation system of marine engine room simulator based on fuzzy comprehensive evaluation," *J. Dalian Maritime Univ.*, vol. 41, no. 1, pp. 104–108, Feb. 2015.

[9] J. Hu, J. Xiao, and D. Hu, "A study on modelling methods to assess and evaluate simulation based training of ship power systems," *Int. J. Simul., Syst., Sci. Technol.*, vol. 17, no. 31, pp. 21.1–21.7, Jan. 2016.
[10] Z. L. Duan, G. Ren, J. D. Zhang, and H. Cao, "Intelligent assessment for collaborative simulation training in ship engine room," *J. Traffic Transp. Eng.*, vol. 16, no. 6, pp. 82–90, Dec. 2016.
[11] H. Shen, D. Zhang, and H. Cao, "Marine engineering virtual training and evaluation system: A learning tool for marine engineers," *Int. J. Eng. Educ.*, vol. 32, no. 5, pp. 2083–2097, Jan. 2016.
[12] Z. L. Duan, H. Cao, G. Ren, and J. D. Zhang, "Assessment method for engine-room resource management based on intelligent optimization," *J. Mar. Sci. Tech.*, vol. 25, no. 5, pp. 571–580, Jan. 2017.
[13] M. Y. Fan, X. M. Yang, Q. Ma, and D. Y. Wang, "Application of computer brainpower evaluating in flight simulator training," *J. Syst. Simul.*, vol. 25, no. 8, pp. 1811–1815, Aug. 2013.
[14] Z. Yan, "A building management evaluation method based on B-P neural networks," *Open Autom. Control Syst. J.*, vol. 7, no. 1, pp. 1262–1267, Sep. 2015.
[15] K.-H. Chang, Y.-C. Chang, and H.-Y. Chung, "A novel AHP-based benefit evaluation model of military simulation training systems," *Math. Problems Eng.*, vol. 2015, pp. 1–14, Jan. 2015.
[16] C. Fang, H. Ren, and Y. Jin, "New evaluating algorithm of the single ship track when inward/outward port based on ship-handling simulator training," *J. Syst. Simul.*, vol. 28, no. 9, pp. 2201–2806, Sep. 2016.
[17] X. Sun, H. Liu, G. Wu, and Y. Zhou, "Training effectiveness evaluation of helicopter emergency relief based on virtual simulation," *Chin. J. Aeronaut.*, vol. 31, no. 10, pp. 2000–2012, Oct. 2018.
[18] T. Ren, W. Xin, X. Yan, H. Zhao, and T. Zhou, "A method for establishing the combat capability evaluation of SoS based on the extreme learning machine," *Missiles Space Vehicles*, no. 6, pp. 107–111, 2019.
[19] C. Wang, C. Ma, and J. Chang, "Cooperative engagement capability evaluation based on improved wavelet neural network," *Command Inf. Syst. Tech.*, vol. 11, no. 1, pp. 41–45, Feb. 2020.
[20] G. Li, R. Mao, H. P. Hildre, and H. Zhang, "Visual attention assessment for expert-in-the-loop training in a maritime operation simulator," *IEEE Trans. Ind. Informat.*, vol. 16, no. 1, pp. 522–531, Jan. 2020.
[21] J. Huang and D. Zhou, "Design and analysis of an evaluation index system for UAV cooperative combat effectiveness," *J. Xi'an Technol. Univ.*, vol. 40, no. 1, pp. 38–44, Feb. 2020.
[22] L. Zhang, X. Wu, Q. Chen, M. J. Skibniewski, and J. Zhong, "Developing a cloud model based risk assessment methodology for tunnel-induced damage to existing pipelines," *Stochastic Environ. Res. Risk Assessment*, vol. 29, no. 2, pp. 513–526, Feb. 2015.
[23] Q. Ye, S. Li, Y. Zhang, X. Shu, and D. Ni, "Cloud model and application overview," *Comput. Eng. Des.*, vol. 32, no. 12, pp. 4198–4201, 2011.
[24] J.-Q. Wang, L. Peng, H.-Y. Zhang, and X.-H. Chen, "Method of multi-criteria group decision-making based on cloud aggregation operators with linguistic information," *Inf. Sci.*, vol. 274, pp. 177–191, Aug. 2014.
[25] D. Li, C. Liu, and W. Gan, "A new cognitive model: Cloud model," *Int. J. Intell. Syst.*, vol. 24, no. 3, pp. 357–375, Mar. 2009.
[26] J. Chen, S. Zhao, Q. Shao, and H. Wang, "Risk assessment on drought disaster in China based on integrative cloud model," *Res. J. Appl. Sci. Eng. Tech.*, vol. 4, no. 9, pp. 1137–1146, Jan. 2012.
[27] H. J. Lu, Y. Wang, D. Y. Li, and C. Y. Liu, "The application of backward cloud in qualitative evaluation," *Chin. J. Comput.*, vol. 26, no. 8, pp. 1009–1014, Aug. 2003.
[28] P. Wang, X. Xu, S. Huang, and C. Cai, "A linguistic large group decision making method based on the cloud model," *IEEE Trans. Fuzzy Syst.*, vol. 26, no. 6, pp. 3314–3326, Dec. 2018.
[29] C. Xu and X. Pan, "Linguistic multi-attribute group decision making method based on normal cloud similarity," *Comput. Sci.*, vol. 46, no. 6, pp. 218–223, Jun. 2019.
[30] N. D. Pankratova and L. Y. Malafeeva, "Formalizing the consistency of experts' judgments in the Delphi method," *Cybern. Syst. Anal.*, vol. 48, no. 5, pp. 711–721, Sep. 2012.
[31] S. E. Seker, "Computerized argument Delphi technique," *IEEE Access*, vol. 3, pp. 368–380, 2015.
[32] M. Alaa, I. S. M. A. Albakri, C. K. S. Singh, H. Hammed, A. A. Zaidan, B. B. Zaidan, O. S. Albahri, M. A. Alsalem, M. M. Salih, E. M. Almahdi, M. J. Baqer, N. S. Jalood, S. Nidhal, A. H. Shareef, and A. N. Jasim, "Assessment and ranking framework for the English skills of pre-service teachers based on fuzzy Delphi and TOPSIS methods," *IEEE Access*, vol. 7, pp. 126201–126223, 2019.
[33] T. L. Saaty, "Decision-making with the AHP: Why is the principal eigenvector necessary," *Eur. J. Oper. Res.*, vol. 145, no. 1, pp. 85–91, Feb. 2003.
[34] X. Yang, L. Zeng, F. Luo, and S. Wang, "Cloud hierarchical analysis," *J. Inf. Comput. Sci.*, vol. 7, no. 12, pp. 2468–2477, Nov. 2014.
[35] X.-B. Mao, S.-S. Hu, J.-Y. Dong, S.-P. Wan, and G.-L. Xu, "Multi-attribute group decision making based on cloud aggregation operators under interval-valued hesitant fuzzy linguistic environment," *Int. J. Fuzzy Syst.*, vol. 20, no. 7, pp. 2273–2300, Jun. 2018.
[36] C.-B. Li, Z.-Q. Qi, and X. Feng, "A multi-risks group evaluation method for the informatization project under linguistic environment," *J. Intell. Fuzzy Syst.*, vol. 26, no. 3, pp. 1581–1592, 2014.
[37] Y. Yang, R. Liu, Y. Chen, T. Li, and Y. Tang, "Normal cloud model-based algorithm for multi-attribute trusted cloud service selection," *IEEE Access*, vol. 6, pp. 37644–37652, 2018.
[38] O. Kosheleva, V. Kreinovich, and S. N. Shahbazova, "Type-2 fuzzy analysis explains ubiquity of triangular and trapezoid membership functions," in *Proc. World Conf. Soft Comput.*, Baku, Azerbaijan, 2018, pp. 29–31.
[39] A. Gholamy, O. Kosheleva, and V. Kreinovich, "Why triangular and trapezoid membership functions are efficient in design applications," Eng. Fac., Dept. Comput. Sci., Univ. Texas El Paso, El Paso, TX, USA, Tech. Rep. UTEP-CS-18-57, Jul. 2018.
[40] M. Wang and D. Niu, "Research on project post-evaluation of wind power based on improved ANP and fuzzy comprehensive evaluation model of trapezoid subordinate function improved by interval number," *Renew. Energy*, vol. 132, pp. 255–265, Mar. 2019.
[41] H. Ghunaim and J. Dichter, "Applying the FAHP to improve the performance evaluation reliability of software defect classifiers," *IEEE Access*, vol. 7, pp. 62794–62804, 2019.
[42] F. Herrera, E. Herrera-Viedma, and L. Martínez, "A fusion approach for managing multi-granularity linguistic term sets in decision making," *Fuzzy Sets Syst.*, vol. 114, no. 1, pp. 43–58, Aug. 2000.

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