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Warship operational readiness evaluation method based on cloud model

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Abstract: [**Objective**] As the existing operational readiness assessment methods of ships cannot meet the needs of naval mission support, a new assessment method based on the cloud model theory is proposed. [**Methods**] First, in the process of determining the indexes, by the cooperative game weight method, the weights calculated by the analytic hierarchy process (AHP), entropy weight method (EWM), and grey relational analysis (GRA) are used for the cooperative game to fit the combined fixed weight, and variable weight theory is introduced to modify and optimize the fixed weight. The cloud model theory is then introduced, and a fuzzy comprehensive assessment model based on the cloud model is designed using cloud similarity instead of membership degree. Finally, air defense missions are taken as an example to assess the operational readiness of ships. [**Results**] The simulations reveal that under the variable weight mode, the fuzzy comprehensive evaluation results based on the cloud model can accurately reflect the operational readiness of real ships. [**Conclusion**] The results of this study can provide references for the operational readiness assessment of ships.

Key words: operational readiness; variable weight theory; cloud model; fuzzy comprehensive evaluation

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0 Introduction

Operational readiness refers to the capacity of systems/equipment to execute all undertaken missions successfully in both peacetime and wartime [1]. Commanders and senior leaders need to master information on the operational readiness of specific military systems in real time for corresponding decision-making, which requires the support of operational readiness evaluation technologies.

At present, the Chinese navy has adopted availability as a measure of operational readiness. Conventionally, availability is evaluated by calculating the percentage of operating time in the total mission time of systems, but this method can hardly accurately reflect the actual states of systems. Therefore, there is a huge gap from the mature operational readiness evaluation of the U.S. military. By establishing a highly information-oriented operational readiness evaluation system, the foreign military can master information on the operational readiness of warships servicing at sea in real time, and the system can provide information support for discovering and correcting faults in operational readiness. However, related technologies are under a blockade, failing to provide ideas for studying the operational readiness evaluation methods of Chinese naval ships.

Research on technologies of operational readiness evaluation in China is still in a theoretical stage, and the evaluation is mainly done by mathematical analysis and statistical testing. Operational readiness evaluation based on mathematical analysis is to establish a functional relationship of operational readiness (availability) to indexes and specific conditions by analyzing the correlation between

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influencing factors. Assuming that combat systems were simply linearly interrelated, Cheng et al. [2] analyzed the composition relationship of combat systems and built a mathematical model for the quantitative analysis of operational readiness of these systems. However, this model simply linearizes the interrelation of combat systems, while such interrelation in practical applications is very complex. On the basis of analyzing the relationship between operational readiness and subsystem indexes, Xie et al. [3] constructed a multi-level coordinated optimization model of operational readiness by a modeling method based on multi-dimensional mapping. As can be seen from the above, readiness evaluation methods based on mathematical models can describe functional relationships between readiness and indexes quantitatively. However, with such methods, it is impossible to build accurate evaluation models for complex nonlinear warship systems composed of various electromechanical devices and information systems.

Operational readiness evaluation based on statistical testing is to evaluate the operational readiness of faulty equipment by probabilistic and statistical models of the equipment [4]. Wei et al. [5] constructed a mission-based operational-readiness simulation model by discrete events and Monte-Carlo method to predict the operating characteristics of naval artillery during mission execution. However, it was assumed that the service life and maintenance time of each component obeyed exponential distribution, and thus the model is not universal. Cheng et al. [6] simulated various events of warship equipment by the Monte-Carlo method and constructed a model and an algorithm of comprehensive readiness evaluation using equipment parameters and service rules. However, in order to simplify the algorithm, they assumed that system components would not fail simultaneously and that equipment failure and maintenance time obeyed exponential distribution. Li et al. [7] constructed a logically determined and randomly scheduled program evaluation and review technique (PERT) network and calculated the paths of the PERT network by the Monte-Carlo method. On this basis, they obtained variation curves of operational readiness rates of aircraft fleets with support time. However, under the assumption that the operation duration obeys normal distribution, it is difficult to reflect the actual operating states of aircraft fleets accurately. By SIMLOX and with the operational readiness rate and use availability as evaluation parameters, Li et al. [8] built a mission-oriented operational-readiness evaluation model of aerial power supply vehicles by Monte-Carlo sampling and queuing theory. As methods based on statistical testing generally use functions to predict the random life of warship equipment, they can hardly reflect the actual operating states of warships accurately. With the deepening of research on system-level testing of warships, when warships are in test zones or perform major missions in specific combat scenarios, given real targets, subject matter, and forces, we can calculate some functional indexes of the systems accurately according to specific system-level test schemes and related algorithms. Obtaining real-time states through state evaluation according to real-time test indexes of warship systems has become a new idea for implementing operational readiness evaluation of such systems.

Index-based state evaluation mainly contains the establishment of evaluation systems as well as index acquisition and comprehensive evaluation. Approaches commonly used include the Markov method, Bayesian network method, Dempster-Shafer evidence theory, information fusion, neural network method, and fuzzy comprehensive evaluation. Due to the limitations of testing technology of warship operational readiness, there are generally few sample data of actual operating states of warships. However, except for fuzzy comprehensive evaluation, the above methods all require a large amount of sample data and produce evaluation models of low transparency, which are unable to continuously optimize the evaluation models according to actual situations. Therefore, such methods are not suitable for evaluating the operational readiness of warships.

Fuzzy comprehensive evaluation is an evaluation method based on fuzzy mathematics [9], which can describe fuzzy information quantitatively through membership functions and then solve fuzzy problems. It is characterized by wide application, good operability, high transparency, and easy modification and does not require massive sample data. Thus, in this paper, the fuzzy comprehensive evaluation method is adopted to evaluate the operational readiness of warships. As an excellent evaluation method, fuzzy comprehensive evaluation has been applied in many fields. However, scholars from China and other countries mainly used this method for evaluating transformers, bridges, and equipment of warship systems and seldom used it for evaluating operational readiness of the whole warship systems.

In addition, no unified standard is available to determine membership functions in fuzzy comprehensive evaluation, and the determination is greatly influenced by subjectivity.

As an uncertainty model dealing with the transformation of qualitative/quantitative information, a cloud model can overcome the limitations of membership functions in fuzzy theory and has played a major role in evaluation decision-making. For this reason, cloud models were introduced into fuzzy comprehensive evaluation in this paper. First of all, using cloud models to replace membership functions, this paper designed a cloud-model-based model for fuzzy comprehensive evaluation of operational readiness. Then, by Python programming, relevant algorithms of cloud models were realized, and the parameters in cloud models of evaluation grades and to-be-evaluated data were determined. Finally, on the basis of clarifying the essence of cloud-model similarity, the paper described the similarity of cloud models comprehensively by using quantity-scale effects of cloud droplets and intersection areas of the cloud models, so as to provide support for cloud-model-based operational readiness evaluation of warships.

1 Weight determination based on cooperative game and variable weight theory

An index weight is the objective embodiment of the importance of each index or factor to an evaluated object in an evaluation system. Thus, scientific and reasonable determination of index weights is of great significance to the readiness evaluation of warships.

On the basis of the cooperative game, this paper fitted weights determined by the analytic hierarchy process (AHP) (subjective weighting), entropy weight method (EWM) (objective weighting), and grey rational analysis (GRA), thus obtaining combined weights with higher accuracy [10]. Moreover, the combined weights were modified by introducing variable weights. Fig. 1 illustrates the specific process.

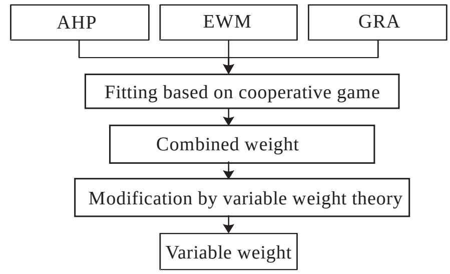


Fig. 1 Weight calculation process

1.1 Mathematical model for weights calculation based on cooperative game

When evaluating the operational readiness of warships, we expect to obtain index weights as close as possible to reality. This paper calculates combined weights by using the game theory under unified constraints, and thus this method is called the cooperative game.

Essentially, the determination of combined weights is to reasonably synthesize calculated results of different weight determination methods, so as to obtain more accurate weights close to reality. Specifically, the determination principle is to minimize total evaluation errors [11].

Mathematically, the cooperative game model is described as follows: Suppose that there are n objects to be evaluated and m evaluation methods available, the set of evaluation methods is M = {1, 2, ..., m}, representing participants in the game. The evaluation value of the k-th object (k = 1, 2, ..., n) obtained by the i-th method (i = 1, 2, ..., m) is denoted as x_{ik}. With the linear average x_k of results from multiple evaluation methods as the benchmark, the error of the i-th evaluation method can be expressed as $E_{ik} = x_k - x_{ik}$. A linearly combined evaluation value based on multiple evaluation methods is given by $\widehat{x}_k = l_1 x_{1k} + l_2 x_{2k} + \cdots + l_i x_{ik} + \cdots + l_m x_{mk}$, where l_i is the weight of an evaluation method.

The error sum of squares $J(M)$ of the combined evaluation model is written as

$$J(M) = \sum_{k=1}^{n} E_k^2 = \sum_{k=1}^{n} \sum_{i=1}^{m} \sum_{j=1}^{m} l_i l_j E_{ik} E_{jk} \tag{1}$$

where E_k is the error of the k-th object; i and j are two different evaluation methods, in which j=1, 2, ..., m, and $i \neq j$.

Let $\boldsymbol{E} = \left(\sum_{k=1}^{n} E_{ik} E_{jk} \right)_{m \times m}$ and $\boldsymbol{L} = (l_1, l_2, \cdots, l_m)^{\mathrm{T}}$, then, Eq. (1) can be simplified to $J(M) = \boldsymbol{L}^{\mathrm{T}} \boldsymbol{E} \boldsymbol{L}$, where $\boldsymbol{E}$ is a sum-of-products matrix of two different evaluation methods, and $\boldsymbol{L}$ is a weighting coefficient vector of m evaluation methods.

With the minimization of the error sum of squares as the optimization objective, an optimally combined evaluation model can be obtained, namely,

$$\begin{cases} \min(J(M)) = \boldsymbol{L}^{\mathrm{T}} \boldsymbol{E} \boldsymbol{L} \\ \boldsymbol{L} \boldsymbol{L}^{\mathrm{T}} = \boldsymbol{I} \\ l_i \geqslant 0 \end{cases} \tag{2}$$

where $\boldsymbol{I}$ is a unit matrix.

According to the average contribution of participants, $J(M)$ is allocated to m participants (namely, evaluation methods). The average contribution is given by

$$\varphi_i(v)=\sum_c \frac{(m-|c|)!(|c|-1)}{m!}[v(c)-v(c-\{i\})] \quad (3)$$

where $\varphi_i(v)$ is the average contribution obtained by the i-th method (participant) alone in the cooperative game $[M, v]$, in which v is the contribution of a participant; $c \in M$, is an alliance of participants; $v(c)$ is the opposite number of $J(c)$, and $J(c)$ is the error sum of squares of the alliance c; $c-\{i\}$ is an alliance excluding the i-th participant; $v(c)-v(c-\{i\})$ is the contribution of the i-th participant.

Upon the normalization of the average contribution, for m evaluation methods, the weight l_i of the i-th method is given by

$$l_i=\frac{v(M)}{\varphi_i(v)}\Big/\sum_{j=1}^{m}\frac{v(M)}{\varphi_j(v)} \quad (4)$$

where $v(M)$ is the negative value of $J(M)$; $\varphi_j(v)$ is the average contribution obtained by the j-th method alone in the cooperative game $[M, v]$.

1.2 Calculation of combined weight based on cooperative game

The calculation of combined weights is to allocate contributions towards evaluation errors under the condition that all participants follow the principle of minimizing evaluation errors, and the determined combined-weight vector is the final payoff vector. Suppose that there are m weight calculation methods participating in the cooperative game and that the weight vector obtained by the i-th method (i = 1, 2, ..., m) is $\boldsymbol{w}^{(i)}=[w_1^{(i)},w_2^{(i)},w_3^{(i)},\cdots,w_n^{(i)}]$, where $w_n^{(i)}$ is the weight of the n-th to-be-evaluated object obtained by the i-th method, the linearly combined weight $\boldsymbol{W}$ from the i-th method is given by

$$\boldsymbol{W}=\sum_{i=1}^{m}\boldsymbol{w}^{(i)}L_{ii} \quad (5)$$

where L_{ii} is the uniform correlation coefficient of the i-th evaluation method.

According to the optimally combined evaluation model of the cooperative game, the combined weight should satisfy $\min\|\boldsymbol{W}-\boldsymbol{w}^{(i)}\|$. According to differential characteristics, the optimal first-order derivative condition is as follows:

$$\sum_{i=1}^{m}\boldsymbol{w}^{(i)}l_i(\boldsymbol{w}^{(i)})^{\mathrm{T}}=\boldsymbol{w}^{(i)}(\boldsymbol{w}^{(i)})^{\mathrm{T}} \quad (6)$$

With average values as reference data of the combined-weight vector, the relationship between the uniform correlation coefficient L_{ii} and each weight can be written as

$$L_{ii}=\frac{\sum_{k=1}^{n}[w_k^{(i)}-\overline{\boldsymbol{w}^{(i)}}][W_k^{(m\_i)}-\overline{\boldsymbol{W}^{(m\_i)}}]}{\left\{\sum_{k=1}^{n}[w_k^{(i)}-\overline{\boldsymbol{w}^{(i)}}]^2\right\}^{1/2}\left\{\sum_{k=1}^{n}[W_k^{(m\_i)}-\overline{\boldsymbol{W}^{(m\_i)}}]^2\right\}^{1/2}} \quad (7)$$

where $w_k^{(i)}$ is the weight of the k-th object, calculated by the i-th method; $\overline{\boldsymbol{w}^{(i)}}$ is the conjugate vector of $\boldsymbol{w}^{(i)}$; $W_k^{(m\_i)}$ is the weight of the k-th object, calculated by $m-1$ evaluation methods (except the i-th method); $\boldsymbol{W}^{(m\_i)}$ is the combined-weight vector of other $m-1$ weights except for $\boldsymbol{w}^{(i)}$; $\overline{\boldsymbol{W}^{(m\_i)}}$ is the conjugate vector of $\boldsymbol{W}^{(m\_i)}$.

1.3 Modification of combined weight based on variable weight theory

In this paper, combined fixed weights determined by the cooperative game method are modified by the equilibrium-coefficient-based variable weight formula proposed in Reference [12], namely,

$$w_d''=\frac{w_d F_d^{\alpha-1}}{\sum_{d=1}^{p} w_d F_d^{\alpha-1}} \quad (8)$$

where d is the number of indexes, and d = 1, 2, ..., p, in which p is the maximum number of indexes; w_d'' is the variable weight of the d-th index; w_d is the fixed weight of the d-th index; F_d is the normalized value of the d-th index; $F_d^{\alpha-1}$ is the $(\alpha-1)$-th power of the normalized value of the d-th index; $0 \leqslant \alpha \leqslant 1$, α is an equilibrium coefficient, and generally $\alpha = 0$.

From Eq. (8), when an index is obviously lower than other indexes, compared with the fixed weight, the variable one will increase obviously, and the final evaluation value will decrease accordingly, which is more in line with the reality.

2 Fuzzy comprehensive evaluation of operational readiness based on cloud theory

In warship systems, there are many index data not conforming to random distribution, such as detection ranges of radar, and it is difficult to describe and process these fuzzy data probabilistically. Fuzzy theory can describe fuzzy characteristics of such uncertain information by fuzzy sets, quantify fuzzy qualitative concepts by membership functions, and clarify fuzzy information by introducing uncertain data into evaluation models for calculation.

Cloud models are the core of cloud theory. Taking into account both fuzziness and randomness, such models can transform uncertainty between qualitative concepts expressed by natural language and their quantitative expressions [13]. Due to the lack of definite specifications for designing membership functions at present, when fuzzy comprehensive evaluation is used for operational readiness evaluation of warship systems, it is necessary to determine membership functions of all indexes according to the experience of experts. Thus, the evaluation results are greatly affected by subjective factors. In contrast, cloud models can be used for the individual evaluation of indexes directly, and their parameters are obtained through specific calculation rules instead of the experience of experts. Thus, the influence of subjectivity is reduced greatly. Therefore, this paper designed a comprehensive evaluation model on the basis of combining cloud models with fuzzy comprehensive evaluation.

2.1 Fuzzy comprehensive evaluation based on normal cloud model

A normal cloud model is one of the most basic cloud models, which uses cloud similarity to measure evaluation results of individual indexes, without the participation of expert experience. Therefore, in this paper, cloud similarity was used to replace membership of the corresponding evaluation grade of each index in fuzzy comprehensive evaluation [14].

Fig. 2 illustrates the structure of the fuzzy comprehensive evaluation model based on normal cloud models. Basic evaluation steps are as follows: 1) determining an evaluation-index set; 2) establishing an evaluation set; 3) determining the parameters in the normal cloud model of each evaluation grade; 4) calculating the parameters in the normal cloud model of to-be-evaluated data; 5) calculating cloud similarity between the cloud model of to-be-evaluated data and that of each evaluation grade; 6) determining index weights; 7) inputting parameters into the fuzzy comprehensive evaluation model to obtain evaluation vectors and then judging results.

2.2 Determination of cloud-model parameters

2.2.1 Cloud generator

A cloud generator is an algorithm for the transformation between qualitative concepts and quantitative values based on cloud theory.

1) Forward cloud generator.

A forward cloud generator mainly functions to map qualitative concepts to quantitative values. Its basic principle is to generate cloud droplets in a precise numerical domain according to the numerical characteristics of clouds, i.e., expectation (*Ex*), entropy (*En*), and hyper-entropy (*He*), as shown in Fig. 3.

The algorithm of a forward cloud generator has the following five basic steps.

Step 1: generating a random number En_e' that obeys the normal distribution with an expectation of En and variance of He^2, where e represents the sample number of cloud droplets, and $e = 1, 2, ..., a$.

Step 2: generating a random number x_e that obeys

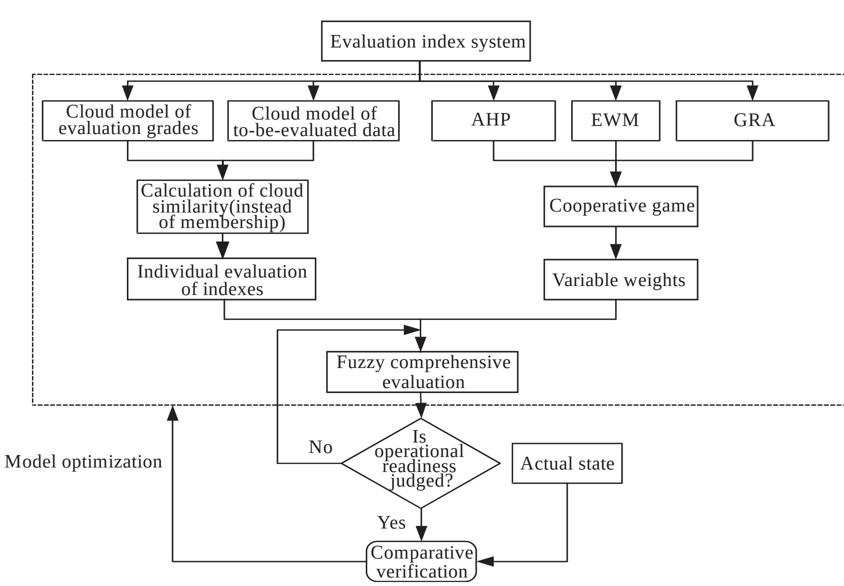


Fig. 2 Fuzzy comprehensive evaluation model based on normal cloud model

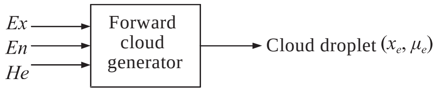


Fig. 3 Schematic diagram of a forward cloud generator

the normal distribution with an expectation of Ex and variance of $En_e'^2$.

Step 3: calculating the membership μ_e of x_e by

$$\mu_e = \mathrm{e}^{-\frac{(x_e - Ex)^2}{2En_e'^2}} \tag{9}$$

Step 4: (x_e, μ_e) is a cloud droplet, representing a random realization of the qualitative concept in the precise domain U.

Step 5: repeating steps 1−4 to generate a cloud droplets totally.

2) Reverse cloud generator.

A reverse cloud generator mainly functions to map quantitative values to qualitative concepts. Its basic principle is to determine numerical characteristics (Ex, En, He) of cloud models according to the calculation of a certain amount of precise data. Fig. 4 illustrates the principle.

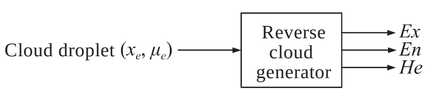


Fig. 4 Schematic diagram of a reverse cloud generator

The reverse cloud generator has the following two basic steps.

Step 1: according to the sample point x_e, calculating the mean, first-order absolute central moment, and variance of samples:

$$\overline{Z} = \frac{1}{a}\sum_{e=1}^{a} x_e \tag{10}$$

$$S_a^2 = \frac{1}{a}\sum_{e=1}^{a} \left| x_e - \overline{Z} \right| \tag{11}$$

$$S^2 = \frac{1}{a-1}\sum_{e=1}^{a} (x_e - \overline{Z})^2 \tag{12}$$

where a is the total number of cloud-droplet samples x_e; $\overline{Z}$ is the sample mean; S_a^2 is the absolute central moment of first-order samples; S^2 is the sample variance.

Step 2: calculating numerical characteristic values Ex, En, He.

$$Ex = \overline{Z} \tag{13}$$

$$En = \sqrt{\frac{\pi}{2}} \times \frac{1}{a}\sum_{e=1}^{a} |x_e - Ex| \tag{14}$$

$$He = \sqrt{S^2 - En^2} = \sqrt{\left(\frac{1}{a-1}\sum_{e=1}^{a}(x_e - \overline{Z})^2\right)^2 - En^2} \tag{15}$$

2.2.2 Determination of cloud models of evaluation grades

At present, no unified standard is available for the classification of operational readiness of warships. According to the classification of warship operational readiness of the U.S. military and opinions of experts, this paper divided the operational readiness of warships into four grades, i. e., "normal", "alert", "abnormal", and "serious".

According to the maintenance and support manual of a specific warship and the opinions of experts, this paper obtained the standard limits of indexes of the warship's combat and command system, classified the indexes into four state intervals, and then built corresponding cloud models of evaluation grades. The basic steps are as follows: 1) randomly generating 5 000 sets of data in the "normal" interval of an index; 2) inputting these random data into the reverse cloud generator to obtain numerical cloud characteristic values of expectation (Ex), entropy (En), and hyper-entropy (He) in the "normal" interval; 3) inputting these characteristic values into the forward cloud generator to obtain the evaluation-grade cloud model of this index in the "normal" interval; 4) repeating the steps 1) – 3) to calculate the numerical cloud characteristic values of other evaluation grades and plot all evaluation-grade cloud models in the same domain. Thus, the data of the overall cloud model is obtained (Table 1).

On this basis, the normal cloud model parameters (Ex_g, En_g, He_g) of each evaluation grade of the warship's air defense system can be determined. Specifically, g = 1, 2, 3, 4, and g means four evaluation grades, namely, "normal", "alert", "abnormal", and "serious" ; Ex_g, En_g, He_g are the expectation, entropy, and hyper-entropy of each evaluation grade of an index, respectively. Fig. 5 and Fig. 6 illustrate the cloud model of evaluation grades of some indexes in the radar system.

2.2.3 Determining cloud model of to-be-evaluated data

The cloud models of to-be-evaluated data and those of evaluation grades are basically generated in the same way. The difference is that the parameters of the former are determined on the basis of the to-be-evaluated test data of a warship system. The basic steps are as follows:

1) Inputting to-be-evaluated test data of a specific state index into the reverse cloud generator to obtain numerical characteristic values of Ex, En, He of the cloud model of to-be-evaluated data.

2) Inputting these numerical characteristic values into the forward cloud generator to obtain the corre-

Table 1 Parameters of the hierarchical cloud model for evaluation of air defense system indexes of ships

System	Index	Normal	Alert	Abnormal	Serious
Radar	Track stability	(2.032, 21.250 3, 0.195 87)	(3.999 6, 1.878 1, 0.133 72)	(6.844 5, 1.853 6, 0.029 128)	(9.498 5, 0.933 69, 0.164 57)
	Detection range/km	(500.96, 62.569, 8.249 3)	(395.81, 61.799, 6.903 1)	(298.72, 62.230, 8.948 1)	(145.38, 95.021, 7.438 2)
	Range accuracy/m	(94.546, 12.273, 1.838 4)	(129.44, 9.125 6, 1.326 4)	(159.84, 11.574, 1.733 4)	(198.02, 10.973, 1.687 5)
	Azimuth accuracy/(°)	(0.307 78, 0.183 69, 0.072 371)	(0.597 74, 0.061 88, 0.023 38)	(0.698 09, 0.061 37, 0.012 391)	(0.953 30, 0.092 23,0.034 195)
Command system	Indication range accuracy/m	(96.369, 11.052, 1.348 2)	(132.44, 10.057 3, 1.058 7)	(164.96, 9.812, 1.934)	(203.14, 12.024, 1.368 7)
	Indication azimuth accuracy/(°)	(0.351 41, 0.121 54, 0.015 243)	(0.612 72, 0.025 78, 0.019 417)	(0.743 54, 0.054 24, 0.016 923)	(1.025 4, 0.071 25, 0.015 635)
	Fusion range accuracy/m	(93.158, 9.157 4, 1.761 2)	(128.42, 8.157 4, 0.935 8)	(158.94, 10.614 7, 1.224 1)	(206.48, 9.444 7, 1.414 5)
	Fusion azimuth accuracy/(°)	(0.297 28, 0.283 78, 0.062 521)	(0.637 25, 0.042 52, 0.017 257)	(0.725 24, 0.055 75, 0.024 748)	(0.982 52, 0.082 57, 0.023 622)
Naval artillery	Target interception range/km	(102.15, 9.158 7, 1.578 4)	(82.348, 10.135 9, 1.264 7)	(67.274 1, 7.569 5, 1.415 6)	(49.154 2, 8.154 3, 1.475 6)
	System response time/s	(2.963 9, 1.458 1, 0.091 48)	(5.143 9, 1.292 5, 0.126 1)	(7.265 9, 1.744 9, 0.091 58)	(10.267, 1.659 1, 0.117 8)
	Pitching accuracy of the control/mrad	(0.091 48, 0.091 21, 0.001 548)	(0.223 91, 0.133 24, 0.001 477)	(0.401 88, 0.117 41, 0.010 216)	(0.532 21, 0.123 17, 0.002 544)
Missile	Target interception range/km	(198.19, 9.315 4, 0.915 43)	(167.63, 7.115 6, 1.741 5)	(131.36, 10.684, 1.125 5)	(98.173 6, 8.147 5, 0.812 56)
	System response time/s	(3.156 4, 1.684 1, 0.083 61)	(5.795 2, 1.365 7, 0.121 5)	(7.513 6, 0.921 64, 0.113 61)	(10.364, 1.352 4, 0.181 4)
	Pitching accuracy of the control/mrad	(0.121 87, 0.086 14, 0.002 541)	(0.257 81, 0.136 21, 0.001 271)	(0.387 32, 0.093 18, 0.008 121)	(0.517 25, 0.136 54, 0.001 325)

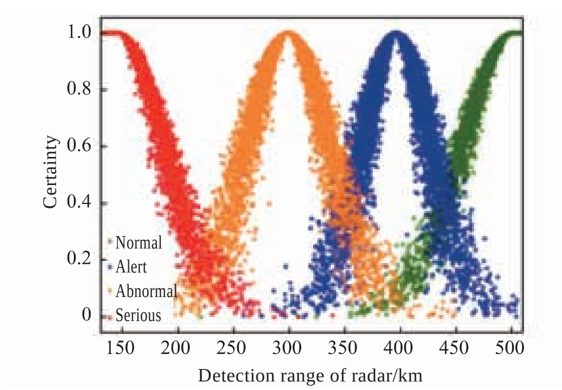


Fig. 5 Normal cloud model of evaluation grades for detection range index of radar

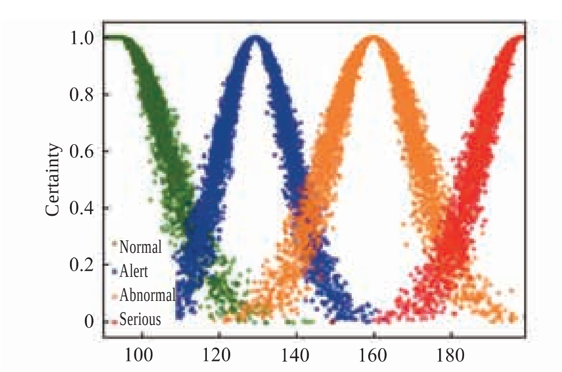


Fig. 6 Normal cloud model of evaluation grades for range accuracy index of radar

sponding cloud model.

2.3 Similarity calculation of normal cloud model

2.3.1 Calculation of the variable *X*

The variable X can be determined by calculating the proportion of the number of cloud droplets of the to-be-evaluated data cloud in the domain ϕ of the evaluation-grade cloud to the total number of cloud droplets of the to-be-evaluated data cloud [15]. Specific steps are as follows:

1) Generating a cloud model of to-be-evaluated data.

A cloud model of to-be-evaluated data is generated by the forward cloud generator. The model contains a cloud droplets in total, and a single cloud droplet is denoted as (x_e, μ_e).

2) Judging whether cloud droplets are in the domain ϕ of the evaluation-grade cloud.

A two-dimensional coordinate system is set, with its x-axis being the cloud droplet x_e and its y-axis being the membership μ_e of the cloud droplet. The boundary of the domain ϕ of the evaluation-grade cloud is composed of uncertain and discrete random cloud droplets. This paper processes the domain ϕ

by approximation and uses a smooth curve to define its boundary [16]. The process is as follows:

(1) In a normal cloud model, 99.7% of the cloud droplets are located in the region enclosed by the inner boundary curve $y_1(x)=\mathrm{e}^{\frac{-(x-Ex)^2}{2(En-3He)^2}}$ and the outer one $y_2(x)=\mathrm{e}^{\frac{-(x-Ex)^2}{2(En+3He)^2}}$[17]. Therefore, when a cloud droplet is located in the region enclosed by the boundary curve $y_2(x)$ and the x-axis, it can be determined that the cloud droplet is in the domain ϕ.

(2) According to the 3En rule of cloud models [17], the range of the domain ϕ along the x-axis can be simplified to $[Ex_{\rm I}-3En_{\rm I},\ Ex_{\rm I}+3En_{\rm I}]$, where $Ex_{\rm I}$ and $En_{\rm I}$ are the expectation and entropy of the data cloud I, respectively.

Upon approximation of the domain ϕ, mathematical constraints can be used to describe whether a cloud droplet of the to-be-evaluated data cloud is in the domain ϕ. In other words, if a cloud droplet (x_e, μ_e) satisfies both $Ex_{\rm I}-3En_{\rm I}\leqslant x_e\leqslant Ex_{\rm I}+3En_{\rm I}$ and $\mu_e \leqslant y_2 x_e$, it is determined that this cloud droplet is in the domain ϕ.

3) Counting the number of cloud droplets of the to-be-evaluated data cloud in the domain ϕ.

4) Repeating the steps 1)−4) and taking the mean $\bar{N}$ of multiple simulation results as the number of cloud droplets of the to-be-evaluated data cloud in the domain ϕ. A cloud model is an uncertainty model. Although the overall characteristics of the cloud model generated each time are basically unchanged, cloud-droplet distribution will change within a certain range randomly. Therefore, the purpose of multiple simulations is to ensure that the "uncertainty" nature of a cloud model is not covered by some random realization.

5) The variable X is given by

$$X=\frac{\overline{N}}{a} \tag{16}$$

2.3.2 Calculation of the variable *Y*

The variable Y can be determined by calculating the area proportion of $\phi\cap\phi'$ in the domain ϕ, where ϕ' is the domain of the to-be-evaluated data cloud. The boundary of $\phi\cap\phi'$ is also composed of random cloud droplets, instead of being a continuous smooth curve. Thus, it is necessary to process the intersection boundary by approximation. According to the basic theory of cloud models, the expectation of a normal cloud model is mathematically expressed by a smooth and continuous curve, and the expectation curve is the main body to characterize qualitative concepts. Thus, during the calculation, the intersected area S' between expectation curves of the to-be-evaluated data cloud and the evaluation-grade cloud can be used for approximate substitution. Specific steps are as follows:

1) Determining the functional expression $s(x)$ of the intersected area S'.

Suppose that $\mu_{\rm I}(x)$ and $\mu_{\rm II}(x)$ are mathematical expectation curves of the evaluation-grade cloud and the to-be-evaluated data cloud, respectively. According to the basic theory of cloud models, we have $\mu_{\rm I}(x)=\mathrm{e}^{\frac{-(x-Ex_{\rm I})^2}{2(En_{\rm I})^2}}$ and $\mu_{\rm II}(x)=\mathrm{e}^{\frac{-(x-Ex_{\rm II})^2}{2(En_{\rm II})^2}}$. Then, the expectation curve $s(x)$ is given by

$$s(x)=\begin{cases}\mu_{\rm I}(x) & (\mu_{\rm I}(x)\leqslant\mu_{\rm II}(x))\\ \mu_{\rm II}(x) & (\mu_{\rm II}(x)<\mu_{\rm I}(x))\end{cases} \tag{17}$$

where $Ex_{\rm II}$ and $En_{\rm II}$ are the expectation and entropy of the data cloud II, respectively.

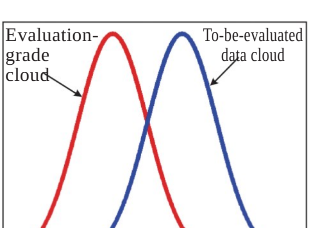
2) Calculating the area of $\phi\cap\phi'$.

Theoretically, the area of $\phi\cap\phi'$ is the integral of the expectation curve $s(x)$ in the interval of $x\in(-\infty,+\infty)$. However, according to the "3En rule" of cloud models, the effective ranges of the evaluation-grade cloud and the to-be-evaluated data cloud along the x-axis are $[Ex_{\rm I}-3En_{\rm I},\ Ex_{\rm I}+3En_{\rm I}]$ and $[Ex_{\rm II}-3En_{\rm II},\ Ex_{\rm II}+3En_{\rm II}]$, respectively. Thus, the integral ranges of $s(x)$ can be simplified according to different intersection cases shown in Fig. 7. Table 2 lists relevant results, where $x_{\min}$ and $x_{\max}$ are the lower and upper limits of the effective integral range of $s(x)$, respectively.

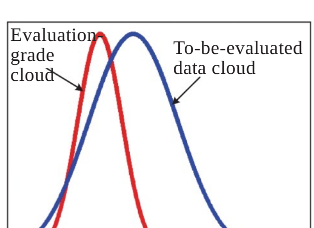
The area S' of $\phi\cap\phi'$ is given by

$$S'=\int_{x_{\min}}^{x_{\max}} s(x)\mathrm{d}x \tag{18}$$

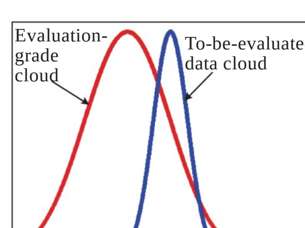
3) The area Y_0 of the domain ϕ is given by



(a) Case 1



(b) Case 2



(c) Case 3

Fig. 7 Different intersection cases of cloud models

Table 2 Effective integral range of $s(x)$

Intersection case	Integral range $[x_{\min}, x_{\max}]$
Case 1	$[Ex_{II} - 3En_{II}, Ex_{I} + 3En_{I}]$
Case 2	$[Ex_{II} - 3En_{II}, Ex_{II} + 3En_{II}]$
Case 3	$[Ex_{I} - 3En_{I}, Ex_{I} + 3En_{I}]$

$$Y_0 = \int_{Ex_I - 3En_I}^{Ex_I + 3En_I} e^{\frac{-(x-Ex_I)^2}{2(En_I)^2}} dx \cong \sqrt{2\pi} En_I \tag{19}$$

4) The variable Y is given by

$$Y = \frac{\int_{x_{\min}}^{x_{\max}} s(x) dx}{Y_0} \tag{20}$$

2.3.3 Combination of cloud-model similarity

As variables X and Y are independent of each other, the vector $\boldsymbol{\lambda} = (X, Y)$ in the two-dimensional coordinate system XY is used to mathematically express cloud-model similarity in this paper. Cloud similarity of 1 means that cloud models of evaluation grades and to-be-evaluated data coincide completely. Numerical cloud-model similarity f_λ is defined as the proportion of the projection length L of any cloud-model similarity vector $\boldsymbol{\lambda} = (X, Y)$ in the direction of the vector $\boldsymbol{\lambda}_0$ (1, 1) to the module of the vector $\boldsymbol{\lambda}_0$, as shown in Fig. 8.

$$f_\lambda = \frac{L}{|\boldsymbol{\lambda}_0|} = \frac{\boldsymbol{\lambda} \cdot \boldsymbol{\lambda}_0}{|\boldsymbol{\lambda}_0| \cdot |\boldsymbol{\lambda}_0|} = \frac{X+Y}{2} \tag{21}$$

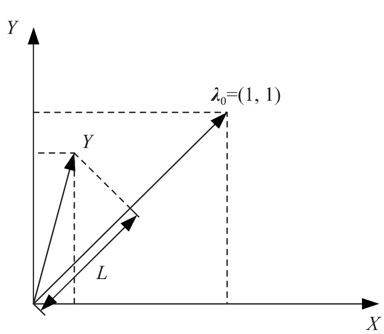


Fig. 8 Vectorization description of cloud similarity

2.4 Fuzzy comprehensive evaluation

According to the cloud similarity algorithm mentioned above, by calculating the similarity between an index cloud model and an evaluation-grade cloud model, we can obtain a cloud similarity vector $\boldsymbol{f} = (f_1, f_2, f_3, f_4)$. Specifically, f_1, f_2, f_3, f_4 are cloud similarity corresponding to the evaluation grades "normal", "alert", "abnormal", and "serious", respectively. By normalizing the cloud similarity vector, we can obtain an evaluation vector (membership vector) $\boldsymbol{S}_d = (f_{1d}, f_{2d}, f_{3d}, f_{4d})$ of an individual index d. Specifically, f_{1d}, f_{2d}, f_{3d}, f_{4d} correspond to the normalized cloud similarity of "normal", "alert", "abnormal", and "serious", respectively. According to the principle of maximum similarity, we can judge the individual evaluation result.

Individual evaluation vectors constitute a matrix $\boldsymbol{S}$ hierarchically, and the weights of all indexes constitute a weight vector $\boldsymbol{W'}$ hierarchically. By combining $\boldsymbol{S}$ and $\boldsymbol{W'}$ through the operation rules of fuzzy comprehensive evaluation, we can obtain a comprehensive evaluation vector, as shown in Eq. (22). As the evaluation index system of this paper is composed of multiple layers, it is necessary to carry out comprehensive evaluation layer by layer from the bottom up. In this way, the evaluation vector $\boldsymbol{B}$ of the operational readiness of the warship can be obtained.

$$\boldsymbol{B} = \boldsymbol{W'} \circ \boldsymbol{S} = [w_1', w_2', \cdots, w_p']_{1\times p} \circ \begin{bmatrix} f_{11} & f_{21} & \cdots & f_{41} \\ f_{12} & f_{22} & \cdots & f_{42} \\ \vdots & \vdots & \cdots & \vdots \\ f_{1p} & f_{2p} & \cdots & f_{4p} \end{bmatrix}_{p\times 4} = [b_1, b_2, b_3, b_4]_{1\times 4} \tag{22}$$

where $\circ$ is the fuzzy operator; w_1', w_2', ..., w_p' are the normalized weight vectors of the index d (d = 1, 2, ..., p); b_1, b_2, b_3, b_4 are evaluation values corresponding to the four evaluation grades (normal, alert, abnormal, and serious), respectively.

3 Example analysis

3.1 Introduction to simulation system

By the prototype of the warship operational readiness state control system (the structure of the information-oriented simulation system is illustrated in Fig. 9), this paper analyzed an application example of operational readiness evaluation to verify the effectiveness of the evaluation model.

The source program of this paper is loaded on a military computer in the operational readiness evaluation system shown in Fig. 9. After the military computer issues a fault injection command, the ship-based system and the test-point channel simulator respond to the command. Then, the main parameters in the index system of operational readiness evaluation are simulated to generate to-be-evaluated data, and the data are transmitted to the military computer via Ethernet.

In Fig. 9, the simulation system of air defense missions is mainly a ship-based system, which is used to simulate combat-system indexes. After receiving a fault injection command from the operational readiness evaluation system, the ship-based simulation environment obtains relevant indexes through simulated warfare and directly transmits

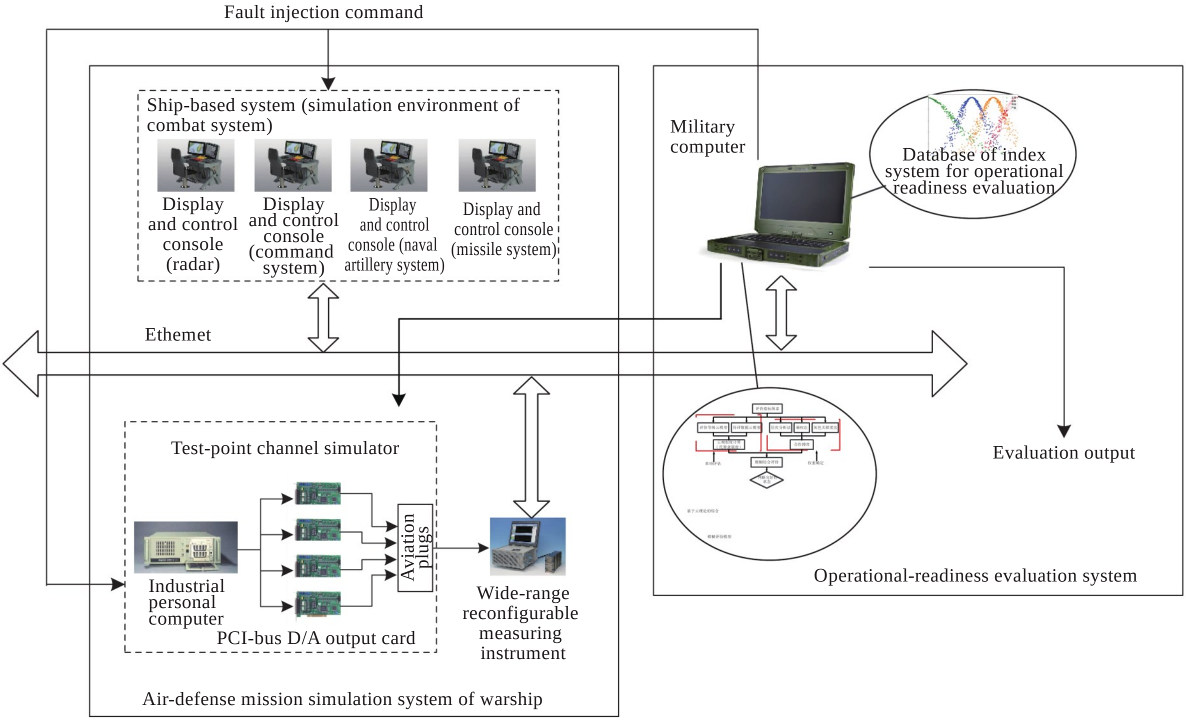


Fig. 9　Structure of warship operational readiness state control system

relevant data to the evaluation system via Ethernet. Upon receiving the fault injection command and the test request command from the upper computer, the test-point channel simulator controls the analog output of D/A cards through an industrial personal computer to simulate the actual output of test signals. Its interface signals are output in a form consistent with reality. A wide-range reconfigurable measuring instrument is used to collect analog signals and convert them into network data, and the data are then transmitted to the evaluation system via Ethernet.

3.2　Simulation process and results

On the basis of the operation-organization relationship of software and hardware in the simulation system in Fig. 9, first, faults including "target indication beyond tolerance", "channel target indication beyond tolerance", and "naval artillery target interception beyond tolerance" were injected into the air defense system. Then, index data of the air defense system were generated through simulation of the ship-based system (Table 1).

The cloud model parameters of to-be-evaluated data were obtained by inputting simulation data of various indexes into the reverse cloud generator. These parameters were normalized according to Eq. (23), and similarity vectors between cloud models of both to-be-evaluated data and evaluation grades were calculated by the similarity algorithm of normal cloud models. With these vectors as individual evaluation results of the indexes, evaluation grades were determined by the principle of maximum similarity. Table 3 lists individual evaluation results of operational readiness indexes of the warship system.

$$F_{kd}(z)=\frac{F_{\text{worst}}-F_{kd}(z)'}{F_{\text{worst}}-F_{\text{best}}} \tag{23}$$

where $F_{kd}(z)$ is the normalized value of the z-th test datum of the d-th index of the k-th evaluation object, in which $z=1, 2, ..., u$(u is the maximum number of test data); $F_{kd}(z)'$ is the z-th test datum of the d-th index of the k-th evaluation object; F_{worst} is the limit value of this index, namely the worst value; F_{best} is the optimal value of this index.

On this basis, cloud similarity vectors of indexes were adopted to replace membership used in fuzzy comprehensive evaluation. The fixed weights determined in this paper were used in the simulation example and were modified to variable ones using normalized average data in Table 3. Given the hierarchical structure of indexes, the fuzzy operation of the cloud-similarity vector matrix and the weight matrix was carried out layer by layer according to Eq. (22). Thus, the comprehensive evaluation results of both component and system layers were obtained. Table 4 and Table 5 list the evaluation results in the case of fixed and variable weights, respectively.

Table 3 Single evaluation result of combat readiness index of ship system

Index	Normalized average data	Individual evaluation result (cloud similarity)	Evaluation grade
Track stability	0.917	(0.906, 0.094, 0, 0)	Normal
Detection range of radar	0.922	(0.911, 0.089 0, 0)	Normal
Range accuracy of radar	0.676	(0.013, 0.346, 0.641, 0)	Abnonmal
Azimuth accuracy of radar	0.747	(0.178, 0.701,0.121, 0)	Alert
Indication range accuracy	0.508	(0,0.269, 0.393, 0.338)	Abnormal
Indication azimuth accuracy	0.632	(0, 0.264, 0.659, 0.077)	Abnormal
Fusion range accuracy	0.897	(0.881, 0.115, 0.004, 0)	Normal
Fusion azimuth accuracy	0.869	(0.826, 0.151, 0.023, 0)	Normal
Naval artillery target interception range	0.698	(0, 0, 0.879, 0.121)	Abnormal
Response time of naval artillery system	0.878	(0.784, 0.211, 0.005, 0)	Normal
Pitching accuracy of naval artillery fire control	0.648	(0, 0, 0.826 0.174)	Abnormal
Missile target interception range	0.815	(0.796, 0.202, 0.002, 0)	Normal
Response time of missile system	0.965	(0.923, 0.077, 0, 0)	Normal
Pitching accuracy of missile fire control	0.946	(0.914, 0.086, 0, 0)	Normal

Table 4 Results of fixed weight evaluation

Index	Comprehensive evaluation vector	Evaluation grade
Radar system (component layer)	（0.509, 0.311, 0.178, 0）	Normal
Command system (component layer)	（0.515, 0.184, 0.215, 0.09）	Normal
Naval artillery system (component layer)	（0.235, 0.063, 0.602, 0.101）	Abnormal
Missile system (component layer)	（0.856, 0.142, 0.001, 0）	Normal
Air defense system (system layer)	（0.576, 0.168, 0.212, 0.054）	Normal

Table 5 Results of variable weight evaluation

Index	Comprehensive evaluation vector	Evaluation grade
Radar system (component layer)	（0.363, 0.375, 0.262, 0）	Alert
Command system (component layer)	（0.315, 0.211, 0.347, 0.127）	Abnormal
Naval artillery system (component layer)	（0.129, 0.051,0.735,0.085）	Abnormal
Missile system (component layer)	（0.806,0.192, 0.002, 0）	Normal
Air defense system (system layer)	（0.370, 0.159, 0.397, 0.074）	Abnormal

3.3 Analysis of results

Table 4 and Table 5 indicate that in terms of the system layer, the evaluation result of the air defense system under fixed weights contradicts that under variable ones, and a few "normal" indexes under fixed weights are judged to be "abnormal" under variable ones. In terms of component layers, the evaluation results of both naval artillery and missile systems under the two weight modes are consistent, while those of both radar and command systems are inconsistent under the two weight modes. The reason for the inconsistency is that the evaluation grades of various indexes remain unchanged under fixed weights after fault injection, while they change accordingly with the fault injection under variable weights.

In addition, in Table 3, the range and azimuth accuracy of radar are greatly lower than other indexes of radar; the indication range and azimuth accuracy of the command system are also significantly lower than other indexes of this system. This is due to the influence of injected faults in the simulation.

Faults injected in the simulation will tremendously affect the air defense system of the warship. Thus, the evaluation result ("normal") of the air defense system under fixed weights is unreasonable, while that ("abnormal") under variable weights is more consistent with the reality, namely that it is more accurate.

4 Conclusions

This paper studied index system construction, index weight determination, evaluation methods, and evaluation models for operational readiness evaluation of warships. In addition, it carried out simulation verification by taking the air defense system of a warship as an example. The main conclusions are as follows:

1) Weight accuracy will be worsened by using a single weight calculation method, and the influence

of abnormal indexes cannot be incorporated into evaluation systems under fixed weights. In view of these problems, this paper introduced a weight calculation method based on the cooperative game and variable weight theory. The combined weights determined by the cooperative game can balance calculated weights of multiple methods, with superiority over the results of a single weight calculation method. After modification with the variable weight theory, the combined weights can avoid inaccurate evaluation results caused by low weights due to index state variations under fixed weights.

2) In view of the high subjectivity in determining membership functions in fuzzy comprehensive evaluation, this paper introduced cloud model theory and designed a cloud-model-based fuzzy comprehensive evaluation model by replacing membership with cloud similarity. The comparison between cloud-model simulation and conventional calculation indicates that the method of this paper produces results consistent with those of conventional methods with high feasibility.

3) According to the simulation results of the prototype of the operational readiness state control system (information-oriented simulation system) of a warship, evaluation results under variable weights are more accurate than those under fixed weights.

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基于云模型的舰船战备完好性评估方法

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摘　要：[**目的**]针对现有的舰船战备完好性评估方法已无法满足海军任务保障需求这一问题,提出基于云模型的新型评估方法。[**方法**]首先,在指标确定过程中,基于合作博弈权重方法,将层次分析法、熵权法和灰色关联度法所计算的权重进行合作博弈,从而拟合得到组合定权重,并引入变权重理论对定权重进行修正优化;然后,引入云模型理论,利用云相似度替代隶属度,设计基于云模型的模糊综合评估模型;最后,以舰船对空防御任务为例,评估舰船战备完好性。[**结果**]仿真结果表明:变权重模式下,基于云模型的模糊综合评估结果可以更准确地反映实船战备状态。[**结论**]研究成果可为舰船战备完好性评估提供参考。

关键词：战备完好性；变权重理论；云模型；模糊综合评估