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ASSESSMENT METHOD FOR ENGINE-ROOM RESOURCE MANAGEMENT BASED ON INTELLIGENT OPTIMIZATION

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Key words: engine-room resource management, intelligent assessment, genetic algorithm, simulator.

ABSTRACT

According to the statistics of the International Maritime Organization, 80% of accidents are related to human factors. To reduce human errors in engine rooms of ships and promote the safety of maritime navigation, the training model and assessment method for engine-room resource management (ERM) were examined in the present study. The man-ship-resource system model and an assessment method based on intelligent optimization are proposed. In this method, the knowledge base, assessment index membership functions, and optimal objective functions were constructed first. The index weights were then computed using the historical assessment data and optimized using the genetic algorithm and game strategy. Finally, after the operational processes and system parameters were confirmed, the fuzzy relationship matrixes were obtained, and the assessment results were produced by multiple fuzzy comprehensive assessment. The method was developed in a 3D collaborative training simulation system. This demonstrated that the method was more capable than others of meeting the special requirements for ERM. The relevant design scheme and technical method have been successfully applied in the engine room assessment system of the national seafarers' assessment center in Shanghai, P. R. China.

I. INTRODUCTION

Marine engine-room resource management (ERM) is an important development in the elimination of human errors in engine rooms and the reduction of marine accidents. In the Manila Amendments to the Seafarers' Training, Certification, and Watchkeeping (STCW) Convention, which went into effect formally in January 2012, ERM is the general principle that should be followed for marine watch duty in order to maintain acceptable standards. ERM has become the mandatory competency standard for maintaining a safe engineering watch, application of leadership and teamwork skills, and using leadership and managerial skills (International Maritime Organization, 2011). Thus, ERM training and assessment have become a new research field.

At present, seafarer competency is still assessed manually, involves a high level of subjectivity, and entails expending substantial human labor and material resources. Intelligent assessment using marine engine simulators and expert systems can not only improve efficiency and save expenses but can also realize automatic checking, recording of operational data, automatic evaluation, and replaying of operational processes. Moreover, it can eliminate subjectivity and improve the fairness of assessment (Zhang et al., 2014).

The Maritime Safety Administration of China has started to reform the assessment model. However, intelligent assessment is still at the research stage. In recent years, some experts have proposed a fuzzy comprehensive evaluation based on a marine engine simulator. However, this method still involves considerable subjectivity in weight determination and can only be used for individual technique assessment. Jiang and Zhao (2011) proposed a method that entails training in daily work and emergency management using an engine room simulator. Jia et al. (2013) demonstrated training and assessment methods and analyzed the types and characteristics of engine room resources. Cao et al. (2014) detailed a comprehensive competence assessment theory for marine engineering training that combines subjective weight factors. On this basis, we proposed the man-ship-resource system model and the intelligent assessment method based on a genetic algorithm.

II. COOPERATIVE TRAINING FOR ERM

According to Chapter III (Standards Regarding the Engine Department) of the Manila Amendments to the STCW Convention, ERM mainly involves allocating and assigning resources, prioritizing tasks, maintaining appropriate assertiveness and leadership, obtaining and maintaining situational awareness, and consideration of team experience, teamwork, and communication. Marine engine room resources can be divided into the fol-

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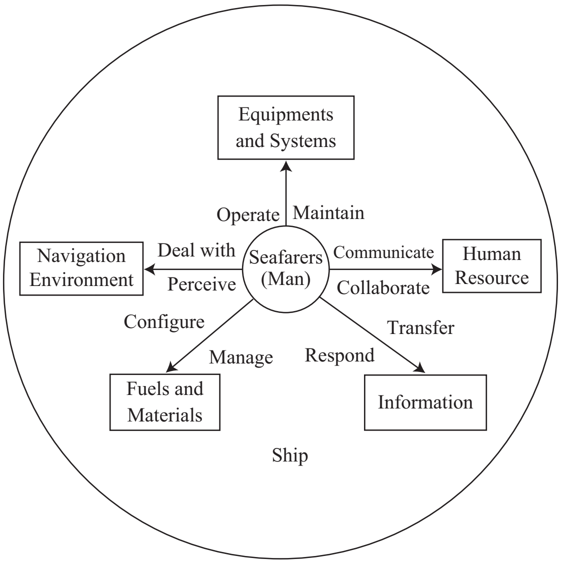

Fig. 1. Man-ship-resource system model.

lowing five categories (Jiang et al., 2011): equipment and system, energy consumption, information and communication, people, and environment.

The seafarers, ship, and all resource types can be regarded as the man-ship-resource system (Fig. 1). Teamwork is the most important factor in the system. Equipment and system resources should be operated, checked, and maintained strictly on schedule and according to standard operating procedures. Energy resources should be configured and updated if necessary. Information resources should be transmitted and fed back effectively. Human resources should be assigned rationally and each member should fulfill his or her role to full capacity. Environmental resources should be understood and addressed effectively. Through collaborative training in different ERM missions, engineering officers should maintain good behavior and habits, work strictly according to procedures, have clear knowledge of their duties, and achieve reductions in the numbers of accidents caused by human error factors.

At present, the training and assessment of ERM are mainly based on the traditional marine engine room simulator. ERM focuses on team cooperation and management, whereas the traditional marine engine room simulator focuses on the training of individual skills (Jia et al., 2013; Cao et al., 2014). Due to the limitations of the training equipment, cooperative training involving multi-role playing is highly dependent on reciting a script. Cooperative training is usually carried out in a training room, and only small groups of a maximum of five persons can participate at the same time. Moreover, the environment of most marine engine simulators is not sufficiently realistic. The training effect is particularly inadequate for seafarers who lack work experience on a real ship.

The Marine Engineering Virtual Simulation Center at Dalian Maritime University of China designed and developed the new DMS-2015 series 3D simulator using virtual reality technology.

Fig. 2. Virtual roaming in the main engine room.

The new simulator avoids the limitations of the traditional simulator. More realistic simulation environments, virtual roaming, and interactive operation are achieved for collaborative training (Lu et al., 2014; Zeng et al., 2014). Trainees can engage in multirole online collaborative training through different network terminals. Virtual roaming in the main engine room is shown in Fig. 2.

III. INTELLIGENT ASSESSMENT FOR ERM

Intelligent assessment is a form of automatic assessment based on artificial intelligence and expert systems, using intelligent algorithms to optimize the evaluation rules and index weights. Moreover, it is capable of intelligent learning (Nie and Wu, 2013; Hrastovec and Solina, 2014). The situation knowledge base and mission knowledge base are created according to assessment requirements. An assessment project using the simulator is determined according to specific situations and missions encountered during actual operation. In accordance with the theory of expert systems, rules are extracted and the rule knowledge base is set up. Each rule corresponds to a set of simulator operation data. The optimization objective functions and the membership functions of the index are constructed for different requirements, and the weights of the evaluation indexes are adjusted using the entropy weight method and historical data (Lin et al., 2012).

Intelligent assessment is the core technology of the system. In the process of assessment, the operation steps, state variables, and other parameters of the system are checked and stored in real time. The data are explained with respect to the corresponding assessment rules, and the assessment results are calculated automatically by using the multiple fuzzy comprehensive evaluation method. By analyzing the historical data, shortcomings can be identified and personalized suggestions can be proposed to improve functioning for the operators. The knowledge base and evaluation rules can also be optimized and improved using historical data. The intelligent assessment scenario is shown in Fig. 3.

In accordance with the STCW Convention and seafarers' competency assessment standards, the engine room collaborative assessment knowledge base was established in combination with the experience of experts. The knowledge base has a hier-

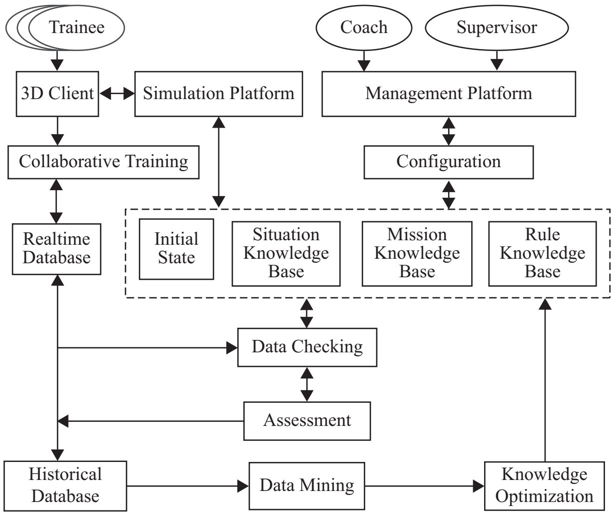

Fig. 3. Intelligent assessment scenario.

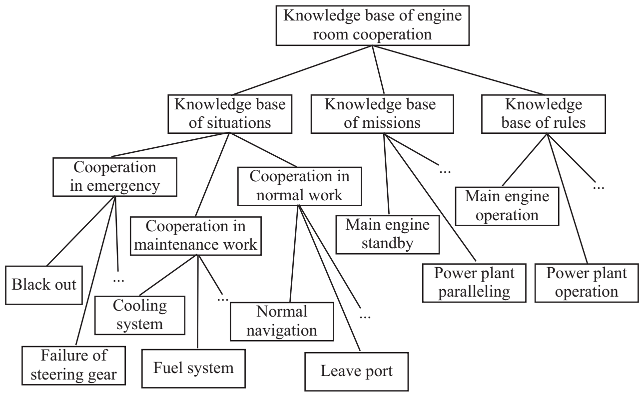

Fig. 4. Structural diagram of intelligent knowledge base.

archical tree structure that is convenient for management and rapid retrieval. The knowledge base is divided into three categories, namely the situation, mission, and rule knowledge bases. The situation knowledge base includes three subsets, namely cooperation in emergency situations, cooperation in normal working situations, and cooperation in maintenance working situations. The mission knowledge base includes the main engine standby set, power plant operation and power supply set, and local control operation set. The rule knowledge base includes the operation sets of the main engine, ship power station, and fuel system. The structure of the assessment knowledge base is presented in Fig. 4.

Knowledge representation is typically used in generative rules. The generative representation mode is generally used in expert systems to indicate reasoning knowledge that has causal relations. This method has the advantage of a simple form, which facilitates not only the extraction of knowledge into rules but also the process of automatic interpretation. The basic form of generative rules can enable definite conclusions on the basis of the former element of reasoning.

The assessment rule is the basis of the system for obtaining assessment results (Yan, 2015). Each of the engine room coordination evaluation rules contains at least one operation or a performance parameter variable. Operations are the specified steps that operators must follow to complete a mission in accordance with the procedures of specific systems or equipment; some operations have proper sequences. The performance parameters are the state parameters triggered by operations. The parameters of each state correspond to a set of numbers or interval values. The state parameters can be preset by the supervisors or coaches. The system records and checks the parameter data of the students' actual operation and the system changes automatically in real time. Further, it automatically determines the accuracy of operations according to the evaluation rules. For example, the system detects that the synchrometer was not closed in time when the operations involving manual synchronous paralleling and disconnecting of the power plant were finished, indicating incorrect operation. The corresponding score is then deducted. At present, there are 39,068 operating variables and performance parameters, and the requirements of the intelligent assessment of engine room cooperation can be achieved.

The assessment of engine room cooperation is complex and the results are fuzzy. The fuzzy comprehensive assessment method can be used to deal with fuzzy problems (Wang and Tan, 2015). In this paper, an intelligent assessment method termed multiple fuzzy comprehensive assessment based on the genetic algorithm (MFCA-GA) is proposed. The steps of the method are as follows:

Step 1: Construct a Multilevel Assessment Factor Set

The assessment factor set is determined according to the situations, missions, and former elements of assessment rules for collaborative training. In view of the more complex process of operations, they are decomposed in the general use of hierarchical processing method, resulting in a number of relatively simple and independent assessment processes. The subset for each of the independent assessment process is then determined. Thus, the multilevel assessment factor set is constructed.

Assumption: $U = (u_1, u_2, \ldots, u_k)$ on behalf of the assessment factor set, and U consists of k components. $u_p = (u_{p1}, u_{p2}, \ldots, u_{pq})$ on behalf of the pth (p = 1, 2, 3, …, k) component, which is made up of q subsets. The final assessment results are obtained from the results of multiple independent processes with multiple levels of weighted aggregation.

Step 2: Construct Assessment Result Set

Assumption: $V = (v_1, v_2, \ldots, v_l)$ is a variety of judgments according to the consequents of assessment rules, called the assessment results set or comment set (Dominelli et al., 2006). The assessment results can be expressed in quantitative scores of the percentage grading system or qualitative comments such as excellent, good, moderate, and bad.

Step 3: Calculate the Underlying Fuzzy Matrix

Assumption: $R_p = (r_{ij})_{q \times l}$ is the fuzzy relation matrix, and

r_{ij} ($i = p_1, p_2, p_3, \ldots, pq$; $j = 1, 2, 3, \ldots, l$) represents the degree of membership of the components of factor u_p relative to the V_j, where $\sum_{j=1}^{l} r_{ij} = 1$. The fuzzy relation matrix R_p from u_p, which is an underlying assessment factor set, to assessment result set V, is determined on the basis of the degree of membership. The pth (p = 1, 2, 3, …, k) underlying fuzzy relation matrix for evaluation is

$$R_p = \begin{bmatrix} R_{p1} \\ R_{p2} \\ \vdots \\ R_{pq} \end{bmatrix} = \begin{bmatrix} r_{p11} & r_{p12} & \cdots & r_{p1l} \\ r_{p21} & r_{p22} & \cdots & r_{p2l} \\ \vdots & \vdots & \vdots & \vdots \\ r_{pq1} & r_{pq2} & \cdots & r_{pql} \end{bmatrix} \quad (1)$$

Step 4: Calculate and Optimize the Weights of the Assessment Index

Assumption: $W = (w_1, w_2, \ldots, w_k)$ on behalf of the final weights vector, and $w_p = (w_{p1}, w_{p2}, \ldots, w_{pq})$ on behalf of the weights vector of the pth (p = 1, 2, 3, …, k) subset. Index weight forms the core of the assessments and affects the results. According to the relative importance of the elements in the assessment index set U and the assessment results, the weights of the assessment indexes are calculated stepwise and optimized using intelligent algorithms.

Step 5: Single Fuzzy Comprehensive Assessment

Assumption: B_p is the underlying assessment results, and the weighted average method, which involves multiplication of the matrix, is used as the model of fuzzy synthetic operation. $B_p = w_p \times R_p$.

Step 6: Multiple Fuzzy Comprehensive Assessment

Assumption: S is the final assessment result that is obtained by weighting the results of multiple evaluations using the weighted average method, namely

$$S = W \times B^{\mathrm{T}} \text{ and}$$

$$B = (B_1, B_2, \ldots, B_k).$$

The membership function is the function that calculates the membership degree of each assessment index corresponding to the assessment results (Chan et al., 1997). There are various methods for determining the membership function, such as the fuzzy statistical, minimum ambiguity, fuzzy distribution, and expert experience methods. In this study, the membership functions of the collaborative assessment of the engine room were designed through the expert experience and fuzzy distribution methods.

1. For the variables of operations and switch states that need to be checked in real time during assessment processes such as the fuel oil viscosity controller mode, lubrication oil temperature control mode, operational mode of the purifier, state of the sea water overboard discharge valve, state of the emergency bilge suction valve, state of the high sea chest filer inlet valve, state of the low sea chest filer inlet valve, state of the condensed water bypass valve, state of the running pump's outlet valve, and the state of the main engine fuel oil return line three-way valve, Boolean functions are used to calculate the membership function, as in

$$A(x) = \begin{cases} 1 & x = p \\ 0 & x \neq p \end{cases} \quad (2)$$

where p is the expected value of the variables of operations and switch states.

2. To ensure the safety of the system and equipment, most of the operating parameters have ideal upper and lower limits. The assessment results would not be optimal if the parameters were above the upper bound or below the lower bound, and the score could even be reduced to zero. The distribution of these variables is the intermediate type of trapezoidal distribution. The trapezoid functions are used for variables such as the voltage, frequency, phase of the power plant, fuel oil viscosity, cooling temperature of the lubricating oil, and fuel oil feed pump outlet pressure, as in

$$A(x) = \begin{cases} 0 & x \leq p_1 \\ \dfrac{x - p_1}{p_2 - p_1} & p_1 < x \leq p_2 \\ 1 & p_2 < x \leq p_3 \\ \dfrac{p_4 - x}{p_4 - p_3} & p_3 < x \leq p_4 \\ 0 & x > p_4 \end{cases} \quad (3)$$

where, p_1, p_2, p_3, and p_4 are the key parameters that can be set by the supervisor.

3. Time duration is the special assessment index in every assessment mission. The variables of time duration, the pressure in the fresh water generator, the pressure in the combustion chamber, and the sea level of the evaporator exhibit a semiridged distribution, and the decreasing ridge types of functions are used, as in

$$A(x) = \begin{cases} 1 & x \leq p_1 \\ \dfrac{1}{2} - \dfrac{1}{2}\sin\dfrac{\pi}{p_2 - p_1}\left(x - \dfrac{p_1 + p_2}{2}\right) & p_1 < x \leq p_2 \\ 0 & x > p_2 \end{cases} \quad (4)$$

where p_1 and p_2 are the key parameters that can be set by the supervisor.

4. In the process of engine room coordination, a change of some operations and switch states might trigger equipment operation and cause numerical changes in the related parameters. Some of the variables exhibit an increasing ridge distribution, such as the fuel and air inlet pressures of the generator and the fresh water flow of the main air cooler, for which increasing ridge type of functions are used to calculate the membership degree, as in

$$A(x) = \begin{cases} 0 & x \le p_1 \\ \dfrac{1}{2} + \dfrac{1}{2}\sin\dfrac{\pi}{p_2 - p_1}\left(x - \dfrac{p_1 + p_2}{2}\right) & p_1 < x \le p_2 \\ 1 & x > p_2 \end{cases} \quad (5)$$

where p_1 and p_2 are the key parameters that can be set by the supervisor.

IV. INTELLIGENT OPTIMIZATION OF WEIGHTS

Entropy weight theory is a type of objective weighting method that applies the concept of entropy in information theory. Entropy reflects the relative importance of indexes in evaluation and reflects the relative competitiveness of each index when the values of all types of evaluation index are given. As a type of objective comprehensive evaluation method, it is widely used to determine the weights of the indexes in accordance with the amount of information transferred to decision makers. According to the degree of variation of each index, the entropy weight of every index is calculated using information entropy. More objective weights are yielded after the weights of the indexes are modified using the entropy weights.

Suppose that a subproject consists of m processes and there is a relative index for each process. There are n trainees as the targets of assessment. The calculation processes for the weight are as follows (Lin et al., 2010; Zeng et al., 2010).

(1) Transform the original score data matrix into a standard matrix $\boldsymbol{Y}$.

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1m} \\ y_{21} & y_{22} & \cdots & y_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ y_{n1} & y_{n2} & \cdots & y_{nm} \end{bmatrix}_{n\times m} \quad (6)$$

(2) Normalize the matrix Y and the matrix $\boldsymbol{Z} = (z_{ij})_{n\times m}$ is obtained. The calculation formula is as follows.

$$z_{ij} = \frac{y_{ij}}{\sum_{i=1}^{n} y_{ij}} \; (i = 1, 2, 3, \ldots, m; j = 1, 2, 3, \ldots, n) \quad (7)$$

(3) Calculate the entropy weights $\boldsymbol{E} = (e_i)_m$ of indexes using the following formula.

$$e_i = -(\ln n)^{-1} \sum_{i=1}^{n} z_{ij} \ln z_{ij} \; (i = 1, 2, 3, \ldots, m; j = 1, 2, 3, \ldots, n) \quad (8)$$

(4) Convert the entropy weights $\boldsymbol{E}$ to the weights of the indexes

$\boldsymbol{W} = (w_i)_{\mathrm{m}}$ using

$$w_i = \frac{1 - e_i}{m - \sum_{i=1}^{m} e_i} \; (i = 1, 2, 3, \ldots, m) \quad (9)$$

where $0 \le w_i \le 1$ and $\sum_{i=1}^{m} w_i = 1$.

The subjective and objective weight methods are the two commonly used means of weight determination. The subjective weight method is based on the emphasis of the experts on the evaluation index, and the objective weight method is based on data from the objective environment. In this study, the analytic hierarchy process (AHP) method was applied to determine the subjective weight vector, and the entropy weight (EW) method was applied to determine the objective weight vector. The weight of the index has a considerable impact on the performance of engine room assessment. In the actual assessment of engine room cooperation, the index weight should be adjusted according to historical assessment data and be optimized intelligently. The steps to optimize weight intelligently are as follows:

Step 1: Determine the Subjective Weight Vector

Assumption: $W_a = (w_{a1}, w_{a2}, \ldots, w_{am})$ on behalf of the subjective weight vector determined with the AHP method.

Step 2: Determine the Objective Weight Vector.

Assumption: $W_e = (w_{e1}, w_{e2}, \ldots, w_{em})$ on behalf of the objective weight vector determined with the EW method.

Step 3: Optimize the Weight Vector Using the Intelligent Algorithm.

$W = (w_1, w_2, \ldots, w_m)$ on Behalf of the Optimal Weight Vector.

Assessment of competency has a critical influence on the qualification of the position and the rank promotion. The scientific methodology and fairness of the results are the most important aspects of carrying out the assessment. In this study, we used the genetic algorithm for the nonlinear optimization and used discrimination of assessment results to indicate the degree of deviation of these results. We determined the minimum weight combination by extracting the optimization objective function. Thus, the deviation of the assessment results was the smallest. In view of the impact of the fairness of the results due to the drawback of a single subjective or objective weight, we proposed the making deviation of the subjective and objective results minimal (MDSORM) weight optimization method.

Assumption: $X_a = (x_{a1}, x_{a2}, \ldots, x_{am})$ on behalf of the proportional vector of subjective weight vector.

Assumption: $X_e = (x_{e1}, x_{e2}, \ldots, x_{em})$ on behalf of the proportional vector of objective weight vector and $x_{ai} + x_{ei} = 1, (i = 1, 2, \ldots, m)$. Vector $\boldsymbol{X_a}$ is the parameter vector to be optimized, and the target function F_1 is as follows:

$$F_1 = \min \sum_{i=1}^{n} \sum_{j=1}^{m} [y_{ij} \times w_{aj} \times x_{aj} - y_{ij} \times w_{ej} \times x_{ej}]^2 \tag{10}$$

$$s.t. \begin{array}{l} x_{aj} + x_{ej} = 1 \\ 0 \le x_{aj} \le 1 \\ 0 \le x_{ej} \le 1 \end{array}$$

China holds the competition that extensively tests seafaring skills once a year or two. One round involves starting a cold ship through an engine room simulator. Teams are required to restore the main propulsion power plant, boilers, and auxiliary equipment to normal operation and analyze the setting faults to exclude them within a specified period of time. In view of this type of assessment, this paper proposes the weight optimization method of determining the deviation of the assessment results maximum (MDARM) and widens their difference. The optimization objective function was extracted and used to optimize the parameter vector through the genetic algorithm. The target function F_2 is as follows:

$$F_2 = \max \sum_{i=1}^{n} \sum_{j=1}^{m} [y_{ij} \times w_{aj} (x_{aj} - \frac{1}{2}) + y_{ij} \times w_{ej} (x_{ej} - \frac{1}{2})]^2 \tag{11}$$

$$s.t. \begin{array}{l} x_{aj} + x_{ej} = 1 \\ 0 \le x_{aj} \le 1 \\ 0 \le x_{ej} \le 1 \end{array}$$

In the decision-making processes for determining the weights, all aspects of the impact of factors should be considered. The game strategy (GS) is typically used to find the consistency and compromise of different weights, and the results are more satisfactory. The deviation between the optimal combination weight and the various weights should be minimized in this method (Huang et al., 2015).

Assumption: There are b different methods for determining the weights, w_s is the weight using the method s, and $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_b)$ is the linear combination weight coefficient vector. The target function F_3 using the GS method is as follows:

$$F_3 = \min \left\| \sum_{s=1}^{b} \alpha_s w_s^{\mathrm{T}} - w_s^{\mathrm{T}} \right\|_2 \quad (s = 1, 2, \ldots, b) \tag{12}$$

V. SIMULATION EXPERIMENT

Ship standby for leaving port was used as an example situation for the assessment in this study. A ship is about to leave port, and a seafarer who is carrying out his watchkeeping duties in the engine room receives a notice of ship standby from the bridge. All the members of the engine department enter the engine room. Eight missions should be completed by the team according to the procedure, namely communication with the bridge, checking the clock and engine bell, operating the ship power plant and supplying power normally, checking the steering gear and rudder, checking and operating the lubricating oil system, checking and operating the fuel system, checking and operating the gas dynamic system, checking and operating the cooling water system, barring, blowing, and a trial run. Each mission includes a series of logically related operational processes.

Ship standby for leaving port is categorized as cooperation during a normal working situation and mainly assesses the competency of teamwork, resource allocation, task allocation, prioritization, situational awareness, and other practical skills. The assessment factor set of ship standby and leaving port consists of eight subsets that comprise several single factors. Thus, the assessment factor set is multiple. Seven collaborative training teams were randomly selected to complete ship standby for leaving port through the virtual engine room collaboration; each team consisted of five members. The traditional percentage grading system was used to produce the assessment results, and the assessment scores of the eight missions of the seven teams were calculated by the single fuzzy assessment, as shown in Table 1.

The subjective weight vector was determined using the AHP method. The objective weight vector was determined on the basis of the EW method and the data in the historical database. We set the population size of the genetic algorithm to 100, the crossover probability to 0.007, and the mutation probability to 0.003. The genetic algorithm was used to optimize the target function of formula (10) and the multiplicative inverse of formula (11); the optimized weight vector was obtained after 500 generations (Shen et al., 2005; Chiu, 2010; Shan et al., 2012). The genetic algorithm was executed in Matlab 7.0 to minimize deviation of the objective and subjective results and maximize the deviation of the assessment results. The fitness curves are shown in Figs. 5 and 6. The target function of formula (12) based on GS was also implemented with Matlab. The weights of each mission are shown in Table 2, and the supervisors or the coaches can choose to set different methods to obtain weights in the management platform.

The results of multiple fuzzy comprehensive intelligence assessment and the results of the manual assessment by assessors

Table 1. Mission scores of ship standby for leaving port (mark).

Team	B1	B2	B3	B4	B5	B6	B7	B8
1	92	81	88	78	80	85	86	89
2	75	80	86	90	70	78	65	88
3	79	41	75	70	45	60	50	78
4	88	89	76	87	90	88	79	97
5	65	70	56	58	67	45	63	50
6	85	83	89	80	79	83	86	84
7	73	67	83	90	93	89	85	75
8	87	83	91	71	75	70	79	76
9	79	65	82	85	60	78	84	77
10	78	82	73	85	86	75	83	87
11	81	65	68	80	79	63	69	84
12	89	68	73	89	87	69	68	76
13	61	59	75	77	81	74	65	83
14	72	96	65	64	85	89	83	81
15	75	71	79	68	58	81	82	80

Table 2. Index weights in different weighting methods.

weighting method	u_1	u_2	u_3	u_4	u_5	u_6	u_7	u_8
AHP	0.0605	0.2491	0.065	0.1799	0.1865	0.1109	0.0708	0.0773
EW	0.1508	0.1107	0.1112	0.1274	0.1211	0.126	0.1418	0.111
MDSORM	0.0621	0.1744	0.0968	0.1733	0.1606	0.1233	0.0997	0.1099
MDARM	0.0693	0.2435	0.1194	0.1394	0.1334	0.1286	0.0786	0.0879
GS	0.0722	0.2311	0.0710	0.1731	0.1780	0.1129	0.0800	0.0817

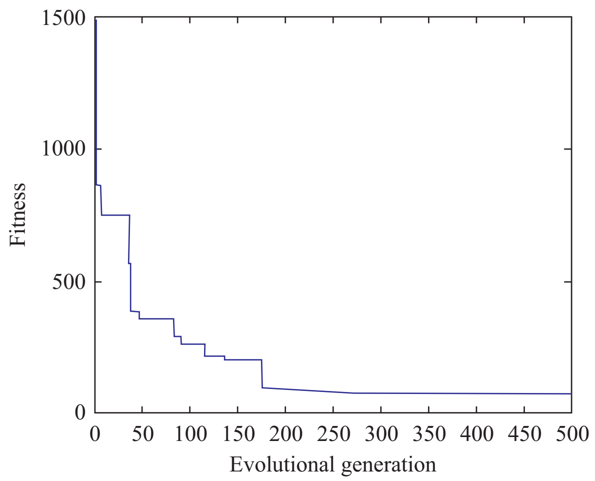

Fig. 5. Fitness curve of the deviation minimization of subjective and objective results.

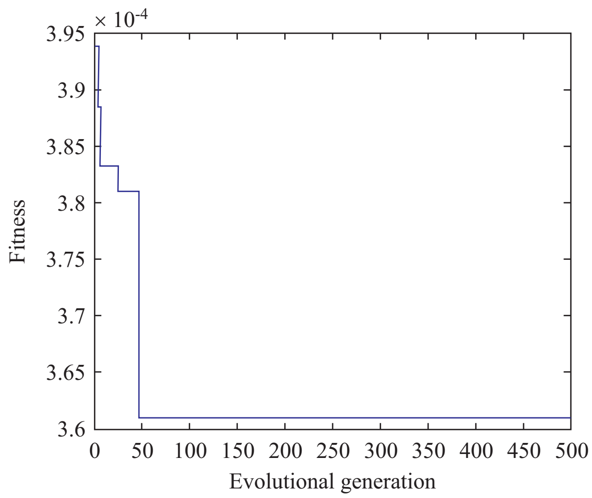

Fig. 6. Fitness curve of the deviation maximization of evaluation results.

are shown in Table 3. The errors of intelligent assessment in different weighting methods and manual assessments are shown in Table 4. The results are contrasted in Fig. 7, which shows that the trends of the comparison curves for the results of the intelligent assessment using the multiple fuzzy comprehensive assessment method and the artificial assessment are consistent and that the data deviation is small. Table 4 indicates that the error of the intelligent assessment based on the genetic algorithm is the smallest and the error of intelligent assessment with weights in the AHP and EW method is larger, with the error of

Table 3. Results of intelligent assessment in different weighting methods and artificial assessment (mark).

Method	AHP	EW	MDSORM	MDARM	GS	Artificial assessment
Team 1	82.810	85.035	83.550	83.657	83.099	88
Team 2	79.356	78.485	79.534	79.698	79.243	80
Team 3	57.077	62.467	59.622	58.671	57.777	56
Team 4	87.721	86.614	87.252	87.022	87.577	93
Team 5	61.255	59.435	59.796	60.385	61.018	63
Team 6	82.515	83.639	82.951	83.227	82.661	84
Team 7	81.722	81.975	82.470	80.947	81.755	83
Team 8	77.845	79.013	77.896	78.899	77.997	82
Team 9	73.332	76.608	75.001	74.348	73.758	78
Team 10	82.140	81.077	81.837	81.226	82.002	77
Team 11	63.631	64.530	64.298	64.369	63.748	65
Team 12	77.646	77.713	77.488	76.353	77.655	75
Team 13	71.446	71.443	72.417	71.009	71.445	75
Team 14	90.284	88.466	89.782	90.461	90.048	93
Team 15	71.381	74.355	72.741	73.029	71.768	75

Table 4. Error of intelligent assessment in different weighting methods and artificial assessment.

Method	AHP	EW	MDSORM	MDARM	GS	Artificial assessment
Average absolute error (mark)	0.856	1.031	0.568	0.465	0.715	2.377
Average relative error (%)	1.175	1.417	0.760	0.603	0.954	3.057
Mean square error (mark)	1.030	1.396	0.669	0.614	0.821	2.657

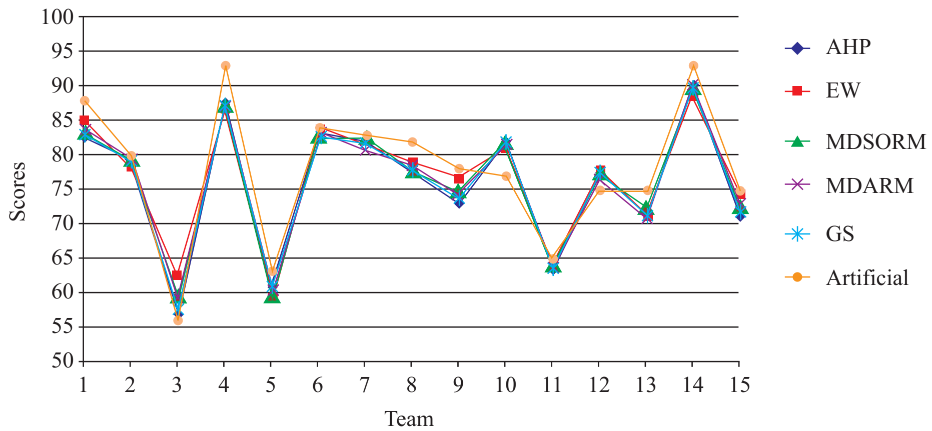

Fig. 7. Contrasting results of the intelligent system and artificial assessment.

artificial assessment being the largest. This indicates that the multiple fuzzy comprehensive assessment method is effective and verifies the validity of intelligent assessment. The results of artificial assessment are evidently more subjective than the results of intelligent assessment. The artificial assessment results of the higher-scoring teams are significantly more favorable than those of the intelligent evaluation of the system, whereas the artificial assessment results of the lower-scoring teams are significantly less favorable. This may be because the artificial assessment enlarges the two extreme results involving subjective impressions.

Some assessment results for the AHP and EW methods are markedly different, with a maximum deviation of 5.39. Single subjective weight has specific subjective and arbitrary aspects, whereas the single objective weight neglects the subjective experience of the experts. Both of these methods have some limitations. The assessment results of the optimized method based on the genetic algorithm deviate somewhat from the results of other methods, and the results indicate that the weight optimized by the genetic algorithm is more reliable. After optimization to minimize the deviation of the objective results and subjective results based on the genetic algorithm, the assessment results of teams 3 and 5 become similar, with a deviation of less than 0.5. Teams 6 and 7, 8 and 12, and 13 and 15 are similar to each other. After optimization to maximize the deviation of the assessment results based on the genetic algorithm, the assessment results of teams 3 and 5 become different, with a deviation greater than 1.7. The deviations between teams 6 and 7, 8 and 12, and 13 and 15 are larger too. This markedly widens the grade of the assessment results. Thus, this method is more suitable for a competitive context. The optimal results based on GS are relatively modest and appear more acceptable.

VI. DISCUSSION AND CONCLUSIONS

According to the data analysis and expert opinions, the intelligent assessment method for engine room collaboration presented in this paper meets the special requirements for the assessment of ERM (Zou and Hu, 2003). The discussion and conclusions are as follows:

(1) For all aspects concerning the impact of factors, the method of optimizing the combination weights using the intelligent algorithm is reasonable, and different target functions are constructed. The optimal results based on GS are relatively modest and more acceptable and reliable. The methods can be used for assessment in the virtual simulation system and the semiphysical simulation engine room. By using the intelligent algorithm to optimize the assessment method based on the marine engine simulator, the engine room cooperation assessment is rendered more scientific and reasonable.

(2) The man-ship-resource system model and the virtual cooperative training model address the shortage of traditional engine room simulators, and have application value, especially for college students who intended to go to sea but lack work experience on a real ship. More than 100 senior seafarers in the engine department have used the virtual engine room in the local area network environment, and the training mode and training system have been adopted to produce the optimal effect. This model and system have been highly rated by experts and can be expected to be widely used.

(3) Deep learning is a newly developed technique that is widely used in the fields of prediction, identification, computer vision, and natural language processing. It can be included in intelligent assessment; however, difficulties persist, such as a lack of training data. The STCW Convention notes that the score or rating method for assessment should be used with caution before being confirmed. We should take advantage of newly developed techniques such as deep learning to improve assessment methods and enhance system performance in conjunction with practical effectiveness. A training center based on cloud services should be established and provide services involving collaboration training and assessment for seafarers, thereby improving their communication and practical operation skills and promoting the safety and efficiency of navigation.

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