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RESEARCH ON PREVENTIVE MAINTENANCE STRATEGIES AND SYSTEMS FOR IN-SERVICE SHIP EQUIPMENT

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ABSTRACT

With continuous improvements in the function and performance of ship equipment, mechanisms of failure have become more and more complicated. To avoid over-maintenance or under-maintenance in existing routine ship maintenance strategies, a ship-level method for repair decisions based on the preventive maintenance concept is proposed in this paper. First, the anticipated repair demand levels of key components are calculated using an improved failure mode and effects analysis (FMEA) method; second, a Weibull distribution model is established, and the parameters are estimated using the maximum likelihood estimation (MLE) to predict the characteristic life of the equipment; then, logical decision principles and rule-based reasoning (RBR) are used to determine the ship repair level and repair timing. Finally, the feasibility and application value of the proposed repair strategy were verified by case studies, and a ship-level system for repair decisions was established.

Keywords: preventive maintenance; FMEA; lifetime prediction; decision system; ship equipment

INTRODUCTION

With continuous improvements in ship equipment technologies since the 21st century, along with increasing frequency of use, the mismatch between the existing ship-level repair modes and maintenance needs has become increasingly apparent [1]. Behind the increasing importance of ship equipment maintenance and support, some urgent problems need to be solved, such as the repair scope, repair level, and repair timing, which have been of concern to the ship equipment maintenance personnel.

At present, the maintenance of ship equipment is mainly performed as scheduled maintenance or temporary repairs, and major scheduled maintenance activities are often carried out in conjunction with ship-level repairs [2]. Ship-level repairs can be divided into three categories according to the scale of the repair work: dock repairs, minor repairs, and medium repairs [3]. During a ship's life cycle, the general ship repair structure is as follows: service - dock repair - minor repair - dock repair - medium repair - dock repair - minor repair - dock repair - decommissioning [4]. The maintenance interval and in-service time for ship-level repairs are typically lengthy, and uniform periodic maintenance strategies are not flexible enough, highlighting an urgent need for preventive maintenance strategies for ship equipment and novel levels of repair modes that combine both periodic and contingent repairs [5-7].

In the field of preventive maintenance, research has been carried out on complex equipment repair decision problems, including determining the repair scope, repair level, and repair timing. Girtler [8] presents a three-state semi-Markov model based on the state transition process of machines in ship power stations, and the applicability of these probabilities in decision-making, with the assistance of the Bayesian statistical theory is demonstrated. Wei [9] proposed a task-oriented preventive maintenance strategy for naval fleets with the lowest maintenance budget as the optimization objective. A model for optimizing situational maintenance decisions to determine the repair scope of the system was established. P. He [10] performed a repair-level analysis of air defence and anti-missile equipment, established a decision flow model based on modular equipment, and applied an improved adaptive particle swarm optimizer (APSO) algorithm to determine the repair level of the equipment. Girtler [11] presents the possibility of controlling the actual operating process of an arbitrary plant installed in a marine power plant based on a four-state semi-Markovian process and the operational decision to determine a rational route for the operating process of the plant based on a dynamic programming method with Bellman's principle of optimality. Zagan [12] develops a multiple linear regression model to describe the effect of historical data on hull repairs, paint time, piping, age, structure and panel replacement to predict a ship's overall maintenance time. Lin [13] introduced a dynamic performance inspection and situational maintenance strategy for the inertial navigation system of a ship. A Wiener process model was used to establish a single-component system performance degradation model for determining the optimal time to repair the system. Hashemi [14] proposed two repair strategies based on the Pólya process, as well as a cost function based on the repair cost of the system, and the system availability was used to obtain the optimal time for preventive maintenance of the system. Niu [15] established a multi-objective optimization model with maintenance frequency as the decision variable. Then, Monte Carlo simulations were used to solve the optimization model and obtain optimal maintenance intervals for parts during their service life. Sa'ad [16] developed an optimal preventive maintenance strategy for minimum repair, which determines the optimal preventive maintenance scope to yield maximum availability. Preventive maintenance of a photovoltaic (PV) plant was taken as an example.

Although the above-mentioned studies have proposed many theories and techniques for preventive maintenance decisions of complex equipment, fewer studies have applied these theories and techniques to repair-mode planning for whole ships. Most existing studies have focused on optimal design of the ship-level repair structure [17], macro reform of the ship-level repair mode, or calculating planned repair intervals; however, the existing models have not been refined enough to determine the scope, class, and timing of whole ship repairs. In this paper, the repair demand level is assessed, and the repair scope of the whole ship is determined using equipment failure information. Furthermore, technical state data and historical failure information of ship equipment are used to determine the remaining life. The repair level and repair timing of the whole ship are also determined using two methods – namely logical decision principles (LDP) and rule-based reasoning (RBR) – and a ship equipment-level repair decision information system is introduced to provide technical support for the repair of ships.

KEY THEORIES AND TECHNIQUES

The repair decision process of ships is based on three aspects: repair scope, repair level, and repair timing. For the repair scope, FMEA is adopted to analyse individually the critical equipment of the ship to determine the level of repair needed for each key component and the degree of impact on the system it belongs to. For assessing the repair level of the whole ship, a logical decision method is adopted. The repair level of the whole ship is determined from the bottom up according to the logical decision diagram and repair scope. For repair timing, the Weibull distribution and maximum likelihood estimation method are adopted to predict the equipment failure time and determine the repair level of the whole ship by generating rules in conjunction with the repair level of the ship.

FMEA

The qualitative FMEA method is particularly well-suited to analysing descriptive information about faults at the phenomenal level, repair information, etc. For ship equipment, FMEA is a better method for making decisions about repair requirements under existing conditions, as the current data collection mostly comprises descriptive data about maintenance phenomena, so accurate sensor measurement data needs to be improved. The core step is to quantify the three indicators of Severity (S), Occurrence (O) and Detection (D) [18-20], and then obtain the risk priority number (RPN) by calculating the product of S, O and D.

However, traditional risk assessment methods have the following limitations or shortcomings: 1) the use of integer values to represent possible levels of risk for different risk factors is too crude and ignores the relative importance of each indicator; 2) risk factors are either not weighted or are difficult to determine; 3) different occurrence, detection, and frequency levels may produce the same RPN values [21-23]. In view of these shortcomings, relative weights can be applied to risk factors as a simple and straightforward method to determine the RPN [24]. In the improved method, the RPN can be expressed as

$$RPN = (k \cdot S)(m \cdot O)(n \cdot D) \tag{1}$$

Owing to the complexity and uniqueness of ships, an overly complex weighting method will greatly increase the economic and time costs. Based on the advice of professional maintenance personnel, this paper adopts ship risk severity k = 0.6, ship risk occurrence m = 0.2, and ship risk detection n = 0.2.

A higher RPN indicates a higher risk of equipment failure in the system and a higher level of maintenance requirements. The evaluation criteria for severity of failure are presented in Table 1.

Tab. 1. Severity of failure rating for ship equipment

Rating	Description of Severity(S)
9,10	Ship cannot be used
7,8	Huge impact on ship systems, making it difficult to work on the ship
5,6	Loss of function of equipment and inability to properly use some ship functions
3,4	Influences use of the equipment
1,2	Does not affect overall use of the equipment

Similarly, evaluation criteria for fault incidence and fault detection can be developed, as described in Tables 2 and 3.

Tab. 2. Failure occurrence rating for ship equipment

Rating	Description of Failure Occurrence (O)
9,10	Mean Time Between Failure (MTBF) of less than 1 week
7,8	MTBF < 1 month
5,6	MTBF < 3 months
3,4	MTBF < 6 months
1,2	MTBF ≥ 6 months

Tab. 3. Failure detection rating for ship equipment

Rating	Description of Likelihood of Detection (D)
9,10	Difficult to detect, requires specialist testing to find
7,8	Needs to be disassembled and tested over a long period of time using a specialized device to find
5,6	Can be detected using detection tools and with professional training
3,4	Can be detected by routine inspection with simple training
1,2	Directly detectable by senses without training

Once the evaluation criteria for S, O, and D have been established, criteria for evaluating the repair need can be developed using the RPN, as shown in Table 4.

Tab. 4. Rating of repair need based on risk priority number (RPN) of ship equipment

Repair Demand Level	Description of RPN
I	0 < RPN < 0.648
II	0.648 ≤ RPN < 3
III	3 ≤ RPN < 8.232
IV	8.232 ≤ RPN < 17.496
V	17.496 ≤ RPN ≤ 24

In Table 4, the RPN is used to divide the repair need of ship equipment into five levels: I–V, where level I is the lowest and level V the highest. A higher level indicates a greater urgency and need for repair. For convenience, equipment with a repair demand level greater than II is collectively referred to as the high-risk part. To avoid confusion between the concepts of the repair level and repair demand level, it should be noted that dock repair, minor repair, and medium repair are classes of large-scale maintenance activities carried out on the whole ship, i.e., repair level; whereas Classes I, II, III, IV and V, as determined by the RPN, are used to classify critical and important equipment of the ship system according to their risk profile and repair need, i.e., the repair demand level.

WEIBULL DISTRIBUTION

To determine the repair time of ship equipment, it is often combined with failure prediction. At present, there are two types of failure prediction methods: (1) emerging methods based on artificial intelligence algorithms [25]; (2) traditional failure prediction methods based on the life distribution of the equipment [26]. Of these, the failure prediction methods based on artificial intelligence algorithms can more accurately estimate equipment life by analysing a large amount of real-time monitoring data; however, this approach is limited by the huge computation load of monitoring the data, and results are difficult to obtain in real time; failure prediction methods based on life distribution can give a more accurate prediction of the time of equipment failure within a certain range, and much less maintenance data is required. Moreover, since the working state of the ship has a certain degree of confidentiality, large quantities of equipment maintenance data and real-time technical state data are difficult to obtain. The failure prediction method presented in this paper to determine the maintenance time of ship equipment is based on the life distribution.

Weibull Distribution Model

The exponential distribution, Weibull distribution, and normal distribution are commonly used to describe the life of a part, with various applications of life distribution. Since the Weibull distribution is a good fit for all types of experimental data and can describe all phases of the bathtub curve, it is often used to describe the life of parts. The failure behaviour of key parts of ship systems, such as bearings, gears, decks, electronic components, motors, engines, transmissions, hydraulic pumps, etc., will typically follow a "bathtub" curve and they will all obey the Weibull distribution [27].

The Weibull distribution can be divided into two types: three-parameter and two-parameter. The three-parameter Weibull distribution is not widely used in practical engineering problems because it requires the use of Newton's iterative method to solve three transcendental equations for estimating the parameters. In addition, the selection of the initial values and parameter evaluation procedure are difficult, and operation data are often scattered. Therefore, the two-parameter Weibull distribution is selected here to describe the life of the ship equipment. The two-parameter Weibull cumulative distribution function is

$$F(t) = 1 - exp\left[-\left(\frac{t}{\theta}\right)^{b}\right], t \geq 0 \quad (2)$$

where b (b> 0) is the shape parameter, which is closely related to the shape of the curve; θ is the scale parameter, θ> 0; and *t* is the time of use of the equipment. Eq. (3) represents the probability of equipment failure before time t.The failure probability density function is given by

$$f(t) = \frac{b}{\theta}\left(\frac{t}{\theta}\right)^{b-1} \cdot exp\left[-\left(\frac{t}{\theta}\right)^{b}\right], t \geq 0 \quad (3)$$

The reliability function is

$$R(t) = exp\left[-\left(\frac{t}{\theta}\right)^{b}\right], t \geq 0 \quad (4)$$

Maximum Likelihood Estimation Method

The unknown parameters of the two-parameter Weibull distribution include both shape and scale parameters. Each reliability index can be calculated only after these parameters are determined. At present, the most widely used parameter estimation method is the method of maximum likelihood estimation (MLE) [28]. The MLE results have high accuracy and can meet the requirements for ship equipment maintenance applications [29]. This method is therefore selected and used to estimate shape parameter b and scale parameter θ of the ship equipment from historical failure data.

The likelihood function of the two-parameter Weibull distribution is

$$L(\theta, b) = \sum_{i=1}^{n} f(t_i) = \prod_{i=1}^{n} \frac{b}{\theta}\left(\frac{t_i}{\theta}\right)^{b-1} \cdot exp\left[-\left(\frac{t_i}{\theta}\right)^{b}\right] \quad (5)$$

The log-likelihood function is obtained by taking the logarithm on both sides, as follows:

$$\ln L = n \ln b - nb \ln \theta + (b-1)\sum_{i=1}^{n} \ln t_i - \frac{1}{\theta^b}\sum_{i=1}^{n} (t_i)^b \quad (6)$$

Taking the partial derivatives of θ and b, respectively, yields

$$\begin{cases} \frac{\varphi \ln L}{\varphi b} = \frac{n}{b} - n \ln \theta + \sum_{i=1}^{n} \ln t_i - \sum_{i=1}^{n}\left(\frac{t_i}{\theta}\right)^{b} \ln\left(\frac{t_i}{\theta}\right) = 0 \\ \frac{\varphi \ln L}{\varphi \theta} = -\frac{nb}{\theta} + \sum_{i=1}^{n}\left(\frac{t_i}{\theta}\right)^{b} \frac{b}{\theta} = 0 \end{cases} \quad (7)$$

By solving this system of non-linear equations with the Newton–Raphson algorithm, the parameter estimation results for θ and b are obtained when the log-likelihood function achieves its maximum value. Unknown θ and b values of the reliability function can be calculated to predict the life of the equipment by calculating each reliability assessment index. Commonly used life indexes include B10, B20, median life (B50), and characteristic life [30]. The characteristic life is the life when the reliability = 0.368 (cumulative probability of failure is 0.632). The characteristic life is often used to describe the overall life of a product. Compared with other life indicators, the characteristic life predicts the maximum possible product life, avoids problems such as over-maintenance, and is more economical. Therefore, the characteristic life as the maximum life of the equipment is adopted in this paper.

LOGICAL DECISION AND RULE-BASED REASONING

Repair Level Decision

The logical decision diagram analysis method is based on the reliability-centred maintenance (RCM) concept, which asks a series of logical questions about the performance indicators of the equipment according to the requirements of the decision objective to decide on the recommended maintenance method. The logical decision diagram is not only highly normative and intuitive, but also flexible and suitable for identifying key characteristics of a design. In this paper, the RCM concept is applied to ship equipment maintenance decision-making. The decision-making process is as follows: first, determine the equipment elements to be considered for maintenance; then input them into the judgment box of the logical decision diagram; finally, complete the analysis and decision-making process by subsequently answering "Yes" or "No" to each question [31]. To determine the repair level of the ship, the repair scope and repair demand level factors obtained using the FMEA method described previously are input into the logical decision diagram, as shown in Fig. 1. The logical decision diagram for the ship repair level is used to determine the repair level of the whole ship.

The constraints for logical determination are the number of faulty parts k, number of systems affected by the risky faulty parts s, and the sum of each fault RPN W ($W = \Sigma PN_k$). To generate the rules for logical determination of the repair level, s and RPN are quantified and assigned values at each repair level. When all fault repair demand levels are I, the corresponding repair level is temporary repair; when there is a repair demand level V among the faulty parts, the corresponding repair level is medium repair. When the number of systems affected by a risky fault component s ≥ 6, the corresponding repair level is medium repair; when the number of systems affected by a risky fault component s ≥ 4, the corresponding repair level is minor repair. For the summation of the RPNs for each fault, W ≥ 100 corresponds to a medium repair, W ≥ 80 indicates a minor repair; W ≥ 40 corresponds to a dock repair, and W < 40 corresponds to a temporary repair. It should be noted that, in practice, the s and RPN thresholds in the above rules can be flexibly adjusted according to the ship situation to suit different ship repair conditions.

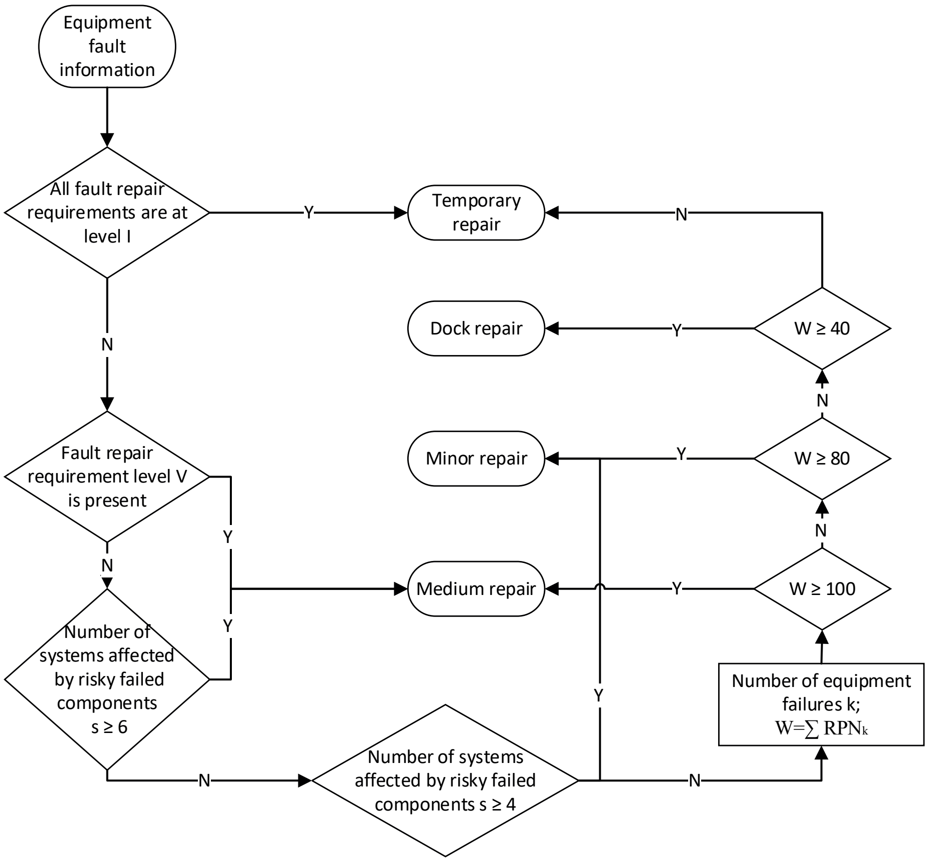

Fig. 1.Repair level logic decision diagram

Reasoning for Timing of Repairs

After predicting the lifespan of key components using the Weibull distribution model, it is necessary to determine the repair time of each key component and the repair timing of the whole ship based on the prediction results. As the ship system is large and complex, the above logical decision method cannot be used to make accurate decisions on the repair timing of the whole ship. Instead, a more rigorous inference method based on generative rules is adopted to determine the repair timing through forward reasoning.

Rule-based reasoning describes relevant expert knowledge or experience as a set of rules representing specific problems in the field and the corresponding answers to those problems. The reasoning process used by experts is simulated to solve a certain problem [32-34]. The method uses a rational decision design approach, which is highly logical and rule-based. Rule-based reasoning is often represented by generative rules because the structure of the knowledge represented by generative rules is closer to human thinking habits and therefore easier to accept and understand. Generative rules are a way of representing knowledge with the help of the conditional IF-THEN statement. In its basic form, the IF-THEN statement can be defined as

$$\begin{gathered} IF \quad \langle P(X_1) \rangle \quad THEN \quad \langle Q(Y_1) \rangle \\ ELSE \quad IF \ \langle P(X_2) \rangle \quad THEN \quad \langle Q(Y_2) \rangle \\ \ldots\ldots \\ ELSE \quad \langle Q(Y_n) \rangle \end{gathered} \tag{8}$$

where P(X) is the conditional assertion (premise) of the generating equation, indicating the state for which the generating equation holds; $Q(Y)$ is the concluding assertion of the generating equation, defining the conclusion or action that follows when the rule holds; $P(X)$ is a logical expression whose value is obtained by a logical operation; when the value of the expression holds true, the action$Q(Y)$ is executed, or the conclusion $Q(Y)$ is obtained. The rules for generating the timing of ship equipment maintenance according to the above representation are as follows:

Rule 1: IF *curtime – sertime < charlife* THEN *repairtime = sertime + charlife* ELSE *repairtime = curtime*

Rule 2: IF *curtime – lastrepair < repairinterval* THEN *repairtime = lastrepair + repairinterval* ELSE *repairtime = curtime*

In the above two rule definitions, *curtime* is the current date, *sertime* is the service date, *charlife* is the characteristic life, *repairinterval* is the repair interval, *lastrepair* is the last repair date, and *repairtime* is the repair date. The difference between the two rules is that Rule 1 determines the repair time for off-weight parts based on the characteristic life predicted by the Weibull distribution, whereas Rule 2 determines the repair time based on the regular maintenance interval of the ship. The rule inference process for the repair time of the ship equipment is shown in Fig. 2.

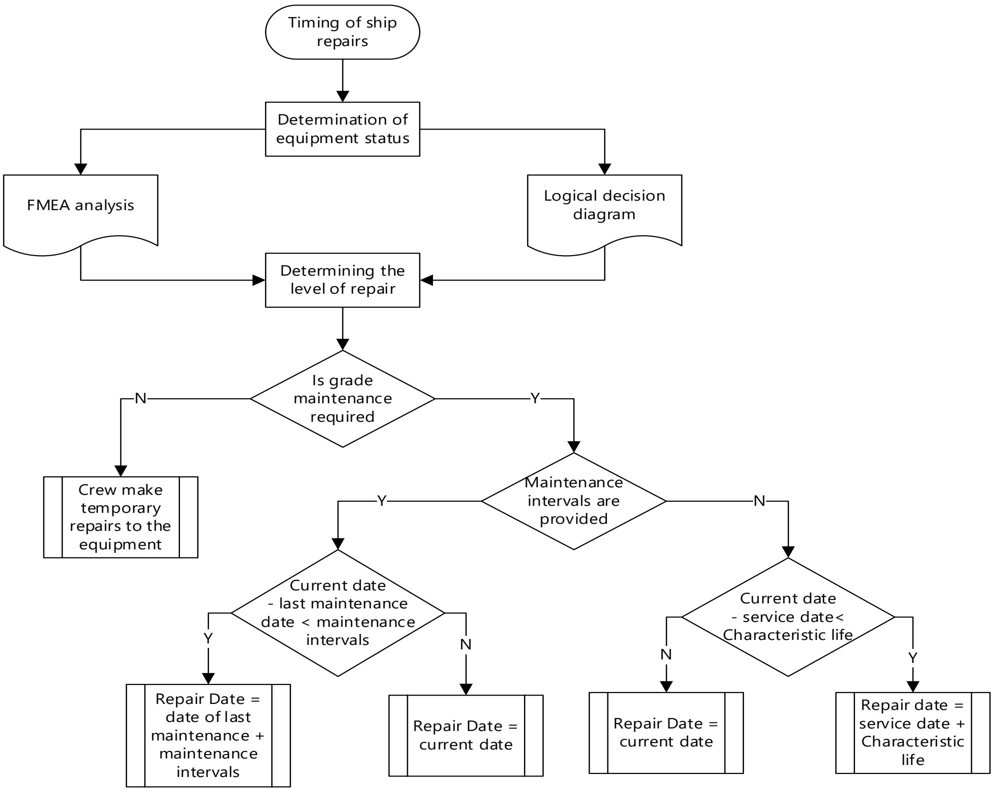

Fig. 2. Decision diagram based on logical reasoning for repair time

By applying the generative rules to the system according to the logic reasoning approach presented in Fig. 2, it is possible to determine the repair timing for equipment and thus the repair timing of the whole ship. The process is as follows: first determine the status of the equipment according to its actual condition, then determine the repair level (i.e. equipment to be repaired) through FMEA and logical decision methods; next, determine whether the large-scale level repairs or small-scale emergency repairs should be carried out on the ship according to the repair level; if emergency repairs are needed, carry out crew-level repairs and replacement work directly without performing the repair time assessment; for equipment level repairs, the repair time is determined according to whether a scheduled maintenance strategy or a preventive maintenance strategy is used. The preventive maintenance strategy matches Rule 1, and the scheduled maintenance strategy matches Rule 2, thus the repair time of the equipment can be obtained through logical reasoning. To determine the repair timing, the nearest equipment repair time to the current date should be selected as the repair timing class for the whole ship.

CASE STUDY

A ship consists of six systems: hull and outfitting, propulsion system, electrical system, auxiliary system, integrated platform management system, and combat system. Each system is made up of several critical components and sub-systems. Of these six systems, the hull and outfitting are important to the overall structure of the ship and dock access, while the electrical and propulsion systems are the ship's source of electrical and kinetic energy, and together, all three systems are highly representative of the overall ship system. Due to the complexity of the ship's systems, the bill of material (BOM) structure for ship maintenance can be divided into three layers: whole ship, system, and key components. Here, several key components are taken as the main research objects, without breaking them down into further sub-components. In this case, the hull structure and outfitting system, the main switchboard of the electrical system, and diesel engine of the propulsion system were selected, and the results were used to develop a bottom-up inference process.

DETERMINATION OF LEVEL OF REPAIR NEED

The FMEA analysis method is described earlier in the paper. In this study, the method was used to analyse the repair information for a fin stabilizer failure provided by the repair shop, high elastic couplings, and diesel generator sets of a certain type of ship. The failure modes and effects were determined, and a risk score was assigned to each failure according to the severity, incidence, and detection evaluation criteria. Finally, the risk of failure score was calculated using the specific RPN value using Eq. (1). Multiple faults often occur in a single off-load component and the RPN for each fault may be different and may correspond to multiple repair demand levels. To solve this problem, the RPNs of multiple faults caused by an off-load component were compared, the maximum value was selected, and the maximum RPN was used to determine the repair demand level, as shown in Table 5.

Tab. 5.Failure mode and effects analysis (FMEA) of key ship components

Equipment	Affiliated System	Failure Mode	Cause Analysis	S	O	D	RPN	Repair Need Level
Fin stabilizer	Hull and outfitting	Press „Start", fins do not work	Faulty oil fill valve, fin drain valve	7	3	8	6.4	III
		Fins do not automatically go into reduced cranking operation	Unlocked locking device, faulty wiring	6	4	9	6.2	
		Fins turned to one side	Servo valve failure, potentiometer damage	5	3	7	5.0	
High elastic couplings	Propulsion system	Rubber fracture	Excessive cabin temperature	3	2	2	2.6	II
		Shaft breakage	Stress greater than permissible value for highly flexible coupling	4	1	1	2.8	
		High elastic damage	Misalignment of shaft system	2	1	4	2.2	
Diesel generator sets	Electrical system	Low starting speed	Poor contact, excessive gear wear	6	6	8	6.4	III
		Strange noise coming from front cover	Excessive backlash	4	5	8	5.0	
		Low oil pressure	Lack of oil, worn piston doors	4	4	7	4.6	

Table 5 shows that the repair demand level for the fin stabilizer is class III, the repair demand level for the high elastic couplings is class II, and the repair demand level for the diesel generator sets is level III, all of which are high-risk parts.

DETERMINATION OF CHARACTERISTIC LIFE

To determine the repair time of key parts, the first step is to carry out a failure prediction of the equipment according to the Weibull distribution model referred to above in the paper and determine the characteristic life of the equipment. The performance of the fin stabilizer is directly related to the ship's manoeuvrability and safety. The historical failure times of 20 fin stabilizers from the same batch of types collected by the ship repair yard are presented in Table 6.

Tab. 6. Failure history of fin stabilizer

Serial number	1	2	3	4	5	6	7	8	9	10
Failure time [day]	173	175	177	183	187	191	196	198	202	205
Serial number	11	12	13	14	15	16	17	18	19	20
Failure time [day]	212	213	221	230	235	240	242	245	246	249

Before using the Weibull distribution model for fault prediction, a data fitting test must be carried out. The Weibull distribution model can only be applied to data with a good fit. The results of fitting tests performed on 20 fault data sets in MATLAB are shown in Fig. 3.

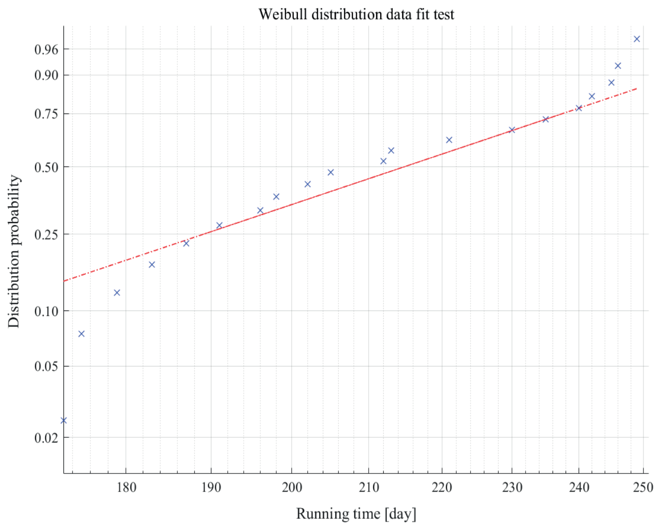

Fig. 3. Goodness-of-fit test results for Weibull distribution

As seen in Fig. 3, the historical failure time data are uniformly distributed along a straight line with a slope greater than zero, indicating that the data distribution conforms to the Weibull distribution. Thus, the failure time of the fin stabilizer can be predicted using the Weibull distribution model. Prior to the failure prediction, parameter estimation must be performed using the greater likelihood estimation method presented above. Briefly, historical failure times were input into the MATLAB program and the non-linear system of equations (Eq. (7)) was solved using Newton's iterative method to obtain $b = 9.480$ and $\theta = 222.422$. The estimated values of b and θ were substituted into Eqs. (3) and (4) to obtain the failure probability density function and reliability function, as follows:

$$f(t) = \frac{9.480}{222.422}\left(\frac{t}{222.422}\right)^{9.480-1} \cdot e^{\left[-\left(\frac{t}{222.242}\right)^{9.480}\right]},\ t \geq 0 \quad (9)$$

$$R(t) = e^{\left[-\left(\frac{t}{222.242}\right)^{9.480}\right]}, t \geq 0 \quad (10)$$

Statistical data for the reliability, failure probability density, remaining life failure probability density, and cumulative probability of remaining life distribution related quantities versus running time were plotted in MATLAB, as shown in Fig. 4.

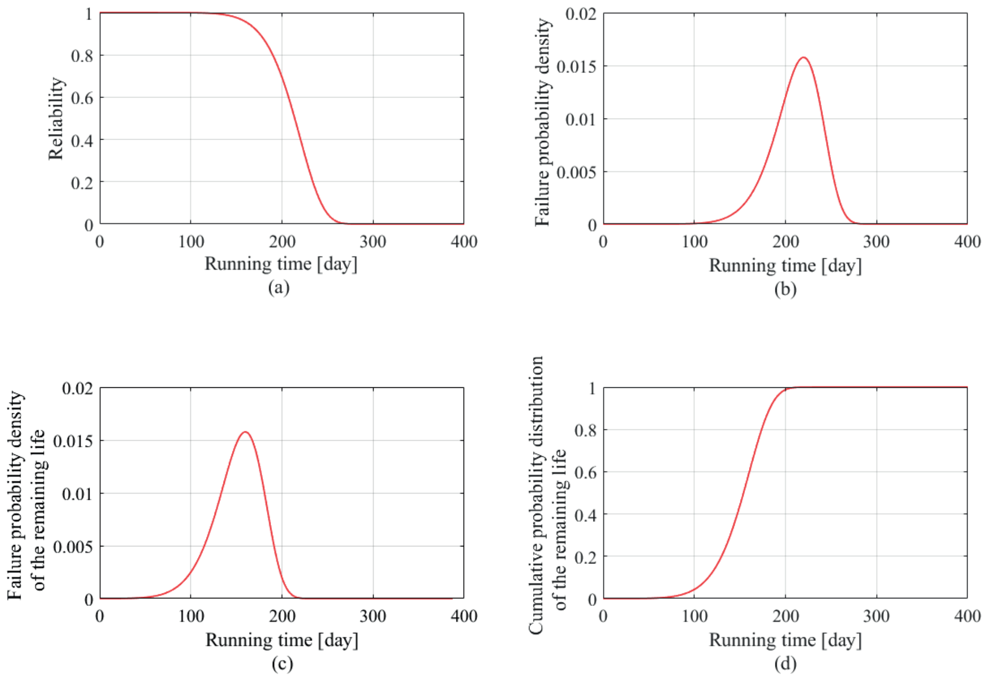

Fig. 4. Statistics related to Weibull distribution for fin stabilizer

Fig. 4(a) shows the variation of reliability of the fin stabilizer with operating time. Using the solve function in MATLAB to solve Eqs. (9) and (10), we can obtain that t = 222.414 days, the reliability is 0.368 and the cumulative probability of failure is 0.632, i.e., the characteristic life is 222 days. Fig. 4(b) shows the variation of the probability density of failure with operating time for the fin stabilizer. It can be concluded that the probability density of failure is greatest at t = 222.414, i.e., the probability of equipment failure is the greatest after this point. Therefore, maintenance should be carried out before then, which also confirms the reasonableness of choosing the characteristic life to predict the equipment maintenance time. Fig. 4(c) and 4(d) show the probability density, cumulative distribution, and running time for the remaining life of the fin stabilizer after 70 days in service. The detailed analysis of these simple functional relationships is not provided here.

Similarly, based on the historical failure time data for the high elastic couplings (421, 462, 485, 502, 531, 552, 571, 599, 625, 650, 662, 683, 701, 715, 730, 733, 750, 772, 780, and 793 days), it can be concluded that b = 6.925, θ= 682.116, and the characteristic life is 682 days. Based on the historical failure time data for the diesel generator sets (243, 249, 255, 260, 262, 269, 275, 287, 290, 295, 305, 307, 310, 316, 320, 330, 331, 335, 338, and 341 days), it can be derived that b= 11.192, θ= 309.868, and the characteristic life is 309 days.

DETERMINATION OF THE LEVEL AND TIMING OF WHOLE SHIP REPAIRS

According to Table 5, the repair scope for a certain type of ship equipment can be obtained. There are 3 high-risk parts in the three systems: the fin stabilizer affects the hull and outfitting, the high elastic couplings of the high-risk part affect the electrical system, and the high-risk diesel generator sets affect the propulsion system. A logical decision analysis of the above scenario was carried out using the approach illustrated in Fig. 1, where the repair demand levels of all three key components are III, WW= ΣRNP_K= 6.4 + 6.2 + 5.0 +2.6 + 2.8 + 2.2 + 6.4 + 5.0 + 4.6 = 41.2, which easily yields a repair level for the ship, namely dock repair.

Once the need for dock repair has been identified, the logical decision diagram in Fig. 2 can be used to make deductive judgements. In the absence of special requirements to use a fixed repair interval, a preventive maintenance strategy is adopted, with each of the off-weight parts obeying Rule 1. By bringing the calculated characteristic life into Rule 1, the repair time of the faulty part can be determined according to the ship's service time and the current date. Finally, the timing of the whole ship repair is determined. The results are presented in Table 7.

Tab. 7. Determination of the timing and level of whole ship.

Name of equipment	Service start time	Current date	Repair interval	Characteristic life	Repair Demand Level	Equipment repair time	Production rule	Timing and level of the whole ship repair
Fin stabilizer	2021-7-1	2021-9-30	none	222	III	2022-2-7	Rule 1	2022-2-7 Dock repair
High elastic coupling	2021-7-1	2021-9-30	none	682	II	2023-5-13	Rule 1	
Diesel generator set	2021-7-1	2021-9-30	none	309	III	2022-5-5	Rule 1	

SYSTEM DEVELOPMENT

Based on the ship repair range generated using the technical state of the ship equipment and fault repair information, the repair level and repair timing decision process and ship equipment level repair decision system process are shown in Fig. 5.

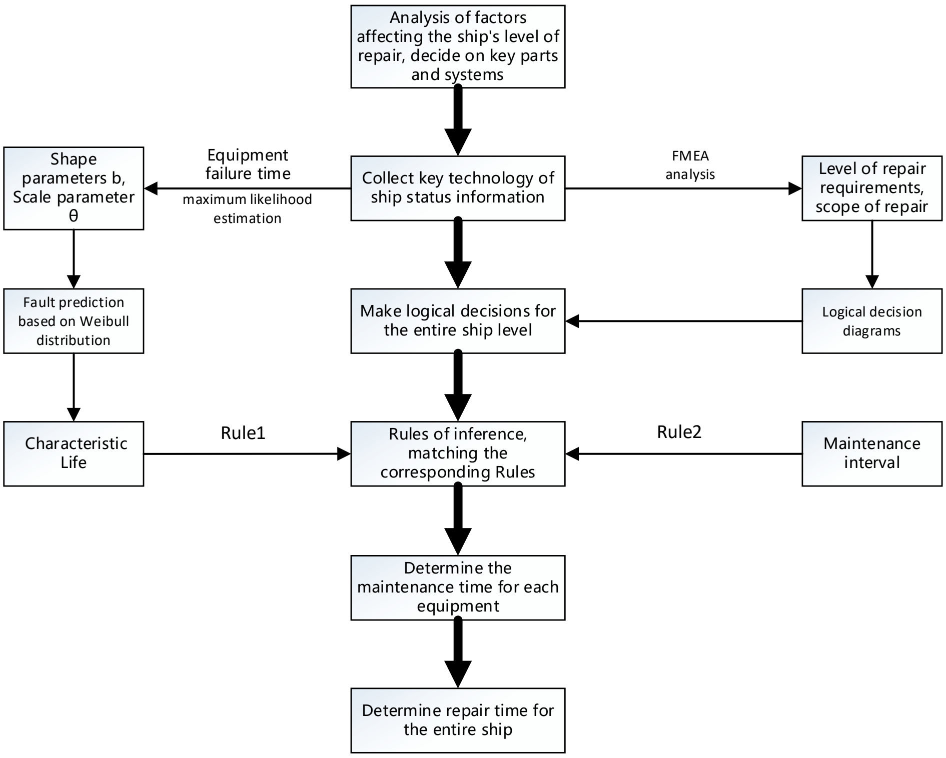

Fig. 5. Data fitting test process for Weibull distribution model

The business process of this system starts from analysing the factors that affect the ship-level repair and distinguishes the important parts and systems that affect the ship-level repair requirements. Then, the technical status information of key parts is collected, and the fault maintenance information and historical fault information of the equipment are screened out. By establishing the repair demand level evaluation criteria, the FMEA method is used to analyse the equipment fault maintenance information and determine the repair demand level and repair scope of the equipment. Finally, the repair level of the whole ship is determined by the logical decision method. Estimation of the shape parameter b and the scale parameter θ of the Weibull distribution is based on the historical failure time of the equipment using the greater likelihood estimation method to carry out the life prediction of the equipment and uses the calculated characteristic life as the result of the failure prediction. If there is no specified repair interval, the preventive maintenance strategy is adopted and the repair time of the equipment is determined by bringing the characteristic life into Rule 1 for rule inference; conversely, if the periodic maintenance strategy is adopted, the repair time of the equipment is determined by bringing the repair interval into Rule 2 for rule inference; finally, the repair time of the equipment is used to determine the repair timing of the whole ship and a report on the ship-level repair decisions is generated.

The system was developed in the Java programming language and MySQL was used to manage the database. The main technical frameworks used were SpringBoot, MyBatis-Plus, and VUE (all three are mainstream technical frameworks used to develop systems in the Java language). The system includes six functional modules: ship management, technical status information management, BOM repair management, repair level analysis, repair demand generation, and system management. Their pair level analysis interface is illustrated in Fig. 6.

The ship repair strategy was validated using a case study of the project management strategy of a ship-level maintenance project. Basic information about the ship, maintenance BOM structure, and technical status data and maintenance information of key parts were imported. According to the defined FMEA evaluation rules, the system automatically calculates the repair timing and repair level of the whole ship, and finally generates a report on the ship's level repair requirements; finally, a ship-level maintenance needs report is generated. In this practical application, the system achieved the expected function and can provide powerful technical support for ship equipment level repair decisions and the management of ship maintenance projects.

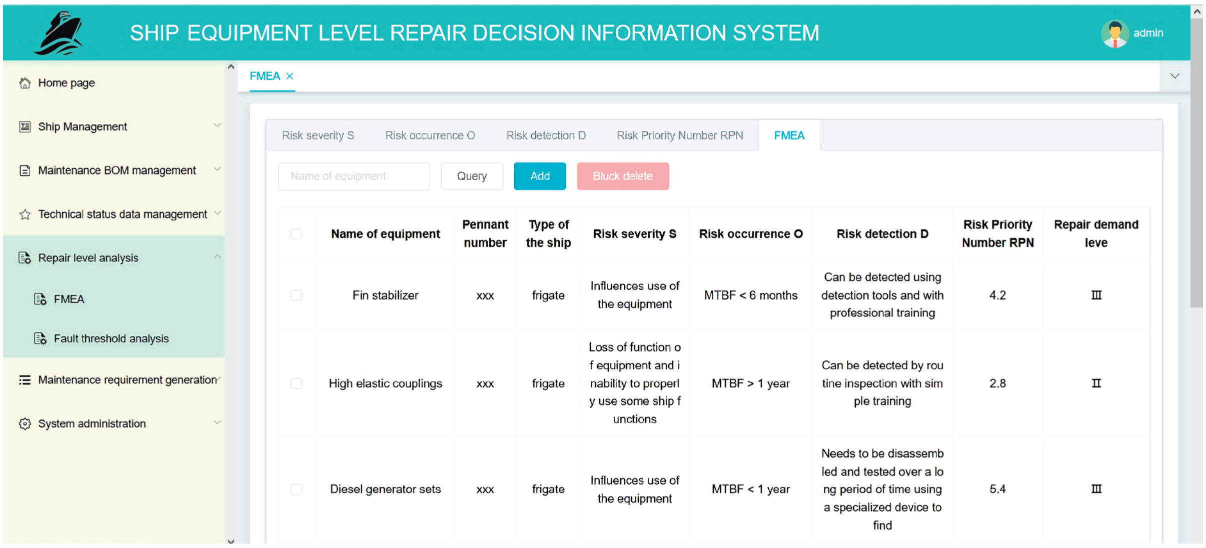

Fig. 6. Repair level analysis interface of system

CONCLUSIONS

Based on existing research on repair levels and the characteristics of ship equipment maintenance, this paper proposed a new decision method for the analysis of the ship equipment repair level. The proposed ship equipment repair level decision process is based on preventive maintenance and can meet the actual repair and maintenance needs of ships better than traditional periodic maintenance strategies. In addition, the accuracy and feasibility of the model and algorithm were verified through case studies of rocker fins and highly flexible couplings, and the repair level and repair timing of the ship were derived.

However, there is still room for improvement in the proposed methods. For example, there are still some qualitative limitations in determining the level of equipment repair needed using FMEA. The next steps will be to continue exploring theoretical and practical methods for decision-making on preventive maintenance that are suitable for ship-level repair. Preventive maintenance with condition monitoring and health management could be combined with artificial intelligence fault prediction algorithms to improve the real-time accuracy of ship equipment repair decisions.

REFERENCES

1. E. Skjong, R. Volden, E. Rodskar, et al., “Past, Present, and Future Challenges of the Marine Vessel’s Electrical Power System”, IEEE Trans. Transp. Electrif., vol. 2, pp. 522–537, 2016.

2. R. Ahmad, S. Kamaruddin, “An overview of time-based and condition-based maintenance in industrial application”, Computers & Industrial Engineering, vol. 63, no. 1, pp. 135-149, 2012.

3. X. Li, Y.X. Jia, Y.S. Bai, “Study on Optimal Maintenance Level Based on Preventive Group Maintenance Police”, Fire Control & Command Control, vol. 38, no. 2, pp. 35-39, 2013.

4. X.C. Li, J.B. Hu, Z.H. Zhang, “Simulation analysis of warship deployability with maintenance structures involved”, Chinese Journal of Ship Research, vol. 10, no. 5, pp. 123-128, 2015.

5. V.J. Jimenez, N. Bouhmala, A.H. Gausdal, “Developing a predictive maintenance model for vessel machinery”, Journal of Ocean Engineering and Science, vol. 5, no. 4, pp. 358-386, 2020, doi: 10.1016/j.joes.2020.03.003.

6. I. Emovon, R.A. Norman, A.J. Murphy, “Hybrid MCDM based methodology for selecting the optimum maintenance strategy for ship machinery systems”, Journal of Intelligent Manufacturing, vol. 29, no. 3, pp. 519-531, 2018.

7. P. Bzura, “Diagnostic Model of Crankshaft Seals”, Polish Marit. Res., vol. 26, no. 3, 2019, doi: 10.2478/pomr-2019-0044.

8. J. Girtler, "Limiting Distribution of the Three-State Semi-Markov Model of Technical State Transitions of Ship Power Plant Machines and its Applicability in Operational Decision-Making", Polish Marit. Res., vol. 27, no. 2, 2020, doi: 10.2478/pomr-2020-0035.

9. R.X. Wei, C. Lin, T.J. Jiang, "Optimization method of condition-based maintenance decision-making for task-oriented ship fleet", Journal of Naval University of Engineering, vol. 33, no. 4, pp. 83-89, 2021.

10. P. He, W. Zuo, Y. Wang, "Modeling for Repair Level of Air and Missile Defense Equipment Under Multi-constraints", Fire Control & Command Control, vol. 45, no. 3, pp. 42-47, 2020.

11. J. Girtler and J. Rudnicki, "The matter of decision-making control over operation processes of marine power plant systems with the use of their models in the form of semi-Markov decision-making processes", Polish Marit. Res., vol. 28, no. 1, 2021, doi: 10.2478/pomr-2021-0011.

12. R. Zagan, I. Paprocka, M.-G. Manea, and E. Manea, "Estimation of Ship Repair Time Using the Genetic Algorithm", Polish Marit. Res., vol. 28, no. 3, 2021, doi: 10.2478/pomr-2021-0036.

13. M.C. Lin, Z. Tang, M.Q. Ning, and C.Y. Wang, "Condition-Based Maintenance Strategy for Dynamic Performance Detection Based on Wiener Process", Journal of Ordnance Equipment Engineering, vol. 42, no. 7, pp. 40-45, 2021.

14. M. Hashemi, M. Asadi, "Optimal preventive maintenance of coherent systems: A generalized Pólya process approach", IISE Transactions, vol. 53, no. 11, pp. 1266-128, 2021.

15. D.P. Niu, L. Guo, et al., "Preventive maintenance period decision for elevator parts based on multi-objective optimization method", Journal of Building Engineering, vol. 44, 2021, doi: 10.1016/J.JOBE.2021.102984.

16. A. Sa'ad, A.C. Nyoungue, Z. Hajej, "Improved Preventive Maintenance Scheduling for a Photovoltaic Plant under Environmental Constraints", Sustainability, vol. 13, no. 18, pp. 10472-10472, 2021.

17. Z. Luo, X. Zhou, Y.D. Shi, "Research on method of warship maintenance structure designing based on requirement of assignment and maintenance", Journal of Naval University of Engineering, vol. 15, no. 04, pp. 60-64, 2018.

18. Y. Geum, Y. Cho, Y. Park, "A systematic approach for diagnosing service failure: Service-specific FMEA and grey relational analysis approach", Mathematical & Computer Modelling, vol. 54, no. 11-12, pp. 3126-3142, 2011.

19. P. Mahdad, A.B. Mohammad, G. Kamran, "An integrated approach for healthcare services risk assessment and quality enhancement", International Journal of Quality & Reliability Management, vol. 37, no. 9/10, pp. 1183-1208, 2019.

20. P.B. Southard, S. Kumar, C.A. Southard, "A modified Delphi methodology to conduct a failure modes effects analysis: a patient-centric effort in a clinical medical laboratory", Quality Management in Health Care, vol. 20, no. 2, pp. 131-51, 2011.

21. Y. Melih, G. Muhammet, C. Erkan, "A holistic FMEA approach by fuzzy-based Bayesian network and best–worst method", Complex & Intelligent Systems, vol. 7, pp. 1547-1564, 2011.

22. S. Boral, S. Chakraborty, "Failure analysis of CNC machines due to human errors: An integrated IT2F-MCDM-based FMEA approach", Engineering Failure Analysis, vol. 130, 2021, doi: 10.1016/J.ENGFAILANAL.2021.105768.

23. E. Kulcsár, I.G. Gyurika, T. Csiszér, "Increasing the Reliability of FMEA Evaluation by Modifying Rating Scales and Applying Pairwise Comparison Method", IOP Conference Series: Materials Science and Engineering, vol. 1190, no. 1, 2021.

24. V. Behnam, M. Salimi, M. Charkhchian, "A new FMEA method by integrating fuzzy belief structure and TOPSIS to improve risk evaluation process", The International Journal of Advanced Manufacturing Technology, vol. 77, no. 1-4, pp. 357-368, 2015.

25. B. Marcia, S. Shankar, et al., "Forecasting fault events for predictive maintenance using data-driven techniques and ARMA modeling", Computers & Industrial Engineering, vol. 115, pp. 41-53, 2018.

26. G. Kai, D. Matthew, et al., Prognostics: The Science of Making Predictions. California, USA, 2017, pp. 123-135.

27. E.M. Assis, E.P. Borges, "Generalized q-Weibull model and the bathtub curve", The International Journal of Quality & Reliability Management, vol. 30, no. 7, pp. 720-736, 2013.

28. A.A. Ahmed, A.R. Zahran, M.A. Ismail, "On maximum likelihood estimation of the general projected normal distribution", Journal of Statistical Computation and Simulation, vol. 91, no. 16, pp. 3453-3472, 2021.

29. P. Nasiri, A.A. Azarian, "Estimation of the Parameters of Generalized Inverse Weibull Geometric Distribution and its Application", Fluctuation and Noise Letters, vol. 20, no. 05, 2021.

30. B.H. Jia, Y.W. Ma, et al., “Continued Operational Safety Assessment of Civil Aircraft Structural Events Based on TARAM”, Advances in Aeronautical Science and Engineering, vol. 12, no. 5, pp. 1-9, 2021, doi: 10.16615/j.cnki.1674-8190.2021.05.04

31. B. Yang, Y. Chen, M.H. Wang, “Discussion about maintenance mode decision method for warship weapon equipments”, Journal of Gun Launch & Control, vol. 35, no. 01, pp. 83-87, 2014.

32. A. Ngamnij, A. Somjit, “Semantic Ontology Mapping for Interoperability of Learning Resource Systems using a rule-based reasoning approach”, Expert Systems with Applications, vol. 40, no. 18, pp. 7428-7443, 2013.

33. E. Ramadhani, H.R. Pratama, E.G. Wahyuni, “Web-based expert system to determine digital forensics tool using rule-based reasoning approach”, Journal of Physics: Conference Series, vol. 1918, no. 4, 2021.

34. K. Ljubica, K. Zoltan, “Using Ontology and Rule-Based Reasoning for Conceptual Data Models Synonyms Detection: A Case Study”, Journal of Database Management (JDM), vol. 30, no. 1, pp.1-21, 2019.

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