Fundamentals and Applications for Risk-Based Design

Makoto ITO*

1. INTRODUCTION

The designs of engineering systems such as ships and aircraft should consider safety as the highest priority. On the other hand, since designs which do not consider economy are unrealistic, how to design attractive and competitive engineering systems while also ensuring safety is important. To achieve this, it is desirable to establish rules with a high degree of freedom, which are capable of incorporating new technologies and concepts, especially in the design of new concept ships.

Risk-based design [1] is an effective concept for ensuring safety in design with high degree of freedom. Risk-based design is based on reliability-based design and uses "risk" as an indicator for setting the criteria of functions such as the upper limit of the probability of failure in structural design. Use of "risk" as an indicator results heightens the universality and transparency of evaluation criteria. Moreover, this approach is also expected to enable countermeasures against unknown phenomena.

In this paper, the structural reliability theory is introduced as the basis for understanding risk-based design, and the difference between reliability-based design and risk-based design is described by using a design optimization problem. In addition, applications of risk-based design are considered. The GBS-SLA (Goal Based Standards-Safety Level Approach) interim guidelines [2] are introduced as an IMO guideline for risk-based structural rules development, after which a method for applying acceptance criteria for fatigue and the technical issues for risk-based structural rules development are explained.

2. STRUCTURAL RELIABILITY THEORY

2.1 General

According to the Japanese Industrial Standards (JIS) [4], reliability is defined as the ability of an item to function as required without fault under the given conditions during the given period. The aim of reliability engineering is to quantify reliability to enable use in system design and maintenance. Concretely, reliability is quantified as the probability that an item will not fail or malfunction.

Structural reliability is reliability for the strength function of structures. In structures, since a fault in the strength function is considered as failure, structural reliability is the property where the state of the structure is not failure. In structural reliability theory, the probability that the structure will fail (probability of failure) is used. According to this definition, the relationship of the probability of failure P_f and reliability R is shown in Eq. (1).

$$P_f = 1 - R \tag{1}$$

If the severity of a failure mode is given by C_D, the quantified risk is formulated as follows:

$$(\text{Risk}) = C_D \times P_f \tag{2}$$

The following sections introduce a calculation method for the probability of failure for cases expressed by a stress-strength model and limit state function, respectively, based on references [5)-7)] of the structural reliability theory.

2.2 Evaluation of Probability of Failure based on Stress-Strength Model

In the structural reliability theory, stress x_s and strength x_r are considered to have uncertainty. Here, we assume that these properties are modeled as independent random variables. In this case, the probability of failure is formulated as follows:

* Research Institute, ClassNK

$$P_f = P[x_r \leq x_s] \tag{3}$$

Now let us consider the evaluation method for the probability of failure in case the stress takes a certain realization (observed value) s. The failure condition occurs when strength x_r is smaller than the realized value of stress s. This is formulated as follows:

$$P_f = \int_0^s f_R(x_r)dx_r = F_R(s) \tag{4}$$

where $f_R(\cdot)$ and $F_R(\cdot)$ are respectively represented as the probability density function and the cumulative distribution function of strength. The probability that the realization of stress is equal to s is formulated as $f_S(s)ds$, where $f_S(\cdot)$ is the probability density function of stress. Therefore, the probability of failure where stress and strength are random variables can be introduced by the integral of Eq. (4) with respect to the realization as follows:

$$P_f = \int_0^\infty F_R(x_s)f_S(x_s)dx_s \tag{5}$$

Next, as a typical example, the case where stress and strength follow independent normal distributions is considered.

$$x_s \sim N(\mu_s, \sigma_s^2) \tag{6A}$$
$$x_r \sim N(\mu_r, \sigma_r^2) \tag{6B}$$

The safety margin x_m, which is the difference between stress and strength, also follows a normal distribution as in Eq. (7).

$$x_m \sim N(\mu_m, \sigma_m^2) \tag{7A}$$
$$\mu_m = \mu_r - \mu_s \tag{7B}$$
$$\sigma_m^2 = \sigma_r^2 + \sigma_s^2 \tag{7C}$$

The failure condition means the safety margin is negative. Therefore, the probability of failure is evaluated as follows:

$$P_f = P[x_m \leq 0] = P\left[\frac{x_m - \mu_m}{\sigma_m} \leq -\frac{\mu_m}{\sigma_m}\right] = \Phi\left(-\frac{\mu_m}{\sigma_m}\right) = \Phi(-\beta) \tag{8}$$

where $\Phi(\cdot)$ is the standard normal cumulative function and β is a reliability index corresponding to the probability of failure. Using Eqs. (6) and (8), the probability of failure is formulated as shown in Eq. (9). As reference, Table 1 shows the relationship of the reliability index and the probability of failure.

$$P_f = \Phi\left(-\frac{\mu_r - \mu_s}{\sqrt{\sigma_r^2 + \sigma_s^2}}\right) \tag{9}$$

Table 1 Reliability index and probability of failure

Reliability index	Probability of failure
1.0	0.159
2.0	2.27×10^{-2}
3.0	1.35×10^{-3}
4.0	3.17×10^{-5}

2.3 Limit State Function Method

In calculating the probability of failure for general structures, the failure condition is often represented by multiple parameters such as the dimensions, material properties and use environment. In this case, the limit state function is frequently utilized to represent the failure conditions mathematically. The limit state function is shown in Eq. (10) using a random vector $\boldsymbol{x} = \left(x_1, \cdots, x_{n_r}\right)^T$ and deterministic vector $\boldsymbol{z} = \left(\boldsymbol{z_1}, \cdots, \boldsymbol{z_{n_d}}\right)^{\boldsymbol{T}}$.

$$g(\boldsymbol{x}, \boldsymbol{z}) \begin{cases} > 0 & \text{safe} \\ = 0 & \text{limit state} \\ < 0 & \text{failure} \end{cases} \tag{10}$$

Using Eq. (10), the probability of failure is formulated as follows:

$$P_f = \int_{g(\boldsymbol{x},\boldsymbol{z}) \leq 0} f_X(\boldsymbol{x}) d\boldsymbol{x} \tag{11}$$

Since an analytical solution of Eq. (11) is generally difficult, several approximation methods have been studied. This paper explains three approaches: The Monte Carlo method (MC), the First Order Reliability Method (FORM) and the Second Order Reliability Method (SORM). MC is a numerical simulation method, whereas FORM and SORM are approaches which approximate limit state functions. In the following discussion, the deterministic vector $\boldsymbol{z}$ is omitted from the equations.

2.3.1 Monte Carlo Method (MC)

MC reproduces pseudo-stochastic phenomena by generating random numbers followed by their probabilistic distributions to evaluate the probability of failure approximately. Since the probability of failure for structural reliability is generally very small, a very large number of random numbers is required in order to obtain probability with sufficient accuracy.

Here, the index function is defined depending on the value of the limit state function as follows:

$$I(\boldsymbol{x}) = \begin{cases} 1, & g(\boldsymbol{x}) \leq 0 \\ 0, & g(\boldsymbol{x}) > 0 \end{cases} \tag{12}$$

The expected value of $I(\boldsymbol{x})$ is evaluated following its definition as shown in Eq. (13).

$$\mathrm{E}[I(\boldsymbol{x})] = \int I(\boldsymbol{x}) f_X(\boldsymbol{x}) d\boldsymbol{x} = \int_{g(\boldsymbol{x})>0} 0 \cdot f_X(\boldsymbol{x}) d\boldsymbol{x} + \int_{g(\boldsymbol{x})\leq 0} 1 \cdot f_X(\boldsymbol{x}) d\boldsymbol{x} = \int_{g(\boldsymbol{x})\leq 0} f_X(\boldsymbol{x}) dx = P_f \tag{13}$$

Eq. (13) means that the expected value of $I(\boldsymbol{x})$ is equal to the probability of failure. The expected value of $I(\boldsymbol{x})$ is the ratio of the number of random numbers (samples) that satisfy the failure condition to the number of generated samples. Assuming the numbers of generated samples and samples that satisfy the failure condition are respectively represented as N and N_f, the approximated value of the probability of failure $\widehat{P_f}$ can be calculated as follows:

$$\widehat{P_f} = \frac{N_f}{N} \tag{14}$$

Since it is obvious that approximate accuracy improves as N is increased, the size of N is determined by an approximation accuracy criterion (threshold). One well-known method uses the coefficient of variety of the probability of failure [7].

2.3.2 First Order Reliability Method (FORM)

FORM linearizes limit state functions (generally non-linear) using the Taylor series and evaluates the probability of failure by using the linearity of the expected value. Since the Taylor series depends on the point of expansion, the choice of this point is important. In the FORM approach, the consistency of the reliability index is assured by choosing the point of expansion on the limit state function.

For simplicity, the random vector $\boldsymbol{x}$ is assumed to follow an independent normal distribution in the following explanation. If this assumption does not hold, the random vector $\boldsymbol{x}$ is approximated as an independent normal distribution by the Rosenblatt transformation [4], and the following discussion is the same.

The standard normal vector using the expected value and the standard deviation of $\boldsymbol{x}$ is represented as $\boldsymbol{u} = \left(u_1, \cdots, u_{n_r}\right)^T$ in Eq. (15), and linear mapping of the limit state function is represented as $G(\cdot)$.

$$u_i = \frac{x_i - \mu_i}{\sigma_i} \quad (i = 1, \cdots, n_r) \tag{15}$$

Here, a point $\boldsymbol{u}^*$, which is on the limit state and is nearest to the origin, is considered. This point is called the Most Probable Point (MPP). The following optimization problem must be solved to obtain MPP.

$$\text{Min.:} \quad \boldsymbol{u}^T \cdot \boldsymbol{u} \tag{16A}$$
$$\text{s.t.:} \quad G(\boldsymbol{u}) = 0 \tag{16B}$$

The Lagrange multipliers method [8] is adopted for the optimization problem in Eq. (16). Using the Lagrange multiplier λ, the necessary condition is as follows:

$$\nabla(\boldsymbol{u}^T \cdot \boldsymbol{u}) + \lambda \nabla G(\boldsymbol{u}) = 0$$
$$\therefore \boldsymbol{u} = -\frac{\lambda}{2} \nabla G(\boldsymbol{u}) \tag{17}$$

Eq. (17) means that the position vector of MPP is directly opposite the gradient vector at MPP (Fig. 1).

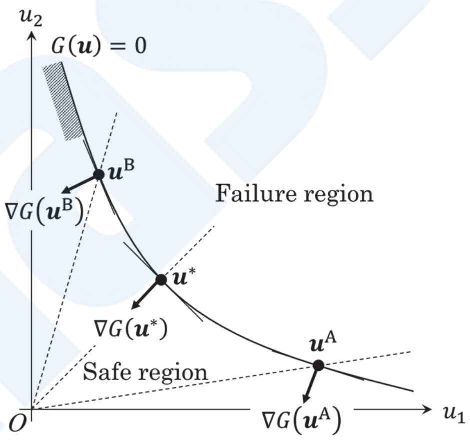

Fig. 1 Relationship between position vectors and gradient vectors

Next, the limit state function is linearized by using the Taylor series about MPP, as follows:

$$G(\boldsymbol{u}) \approx G_l(\boldsymbol{u}) = \nabla^T G(\boldsymbol{u}) \cdot (\boldsymbol{u} - \boldsymbol{u}^*) \tag{18}$$

Since the linearized limit state function $G_l(\boldsymbol{u})$ is the sum of independent random variables, the expected value and its variance are obtained as follows:

$$\mathrm{E}[G_l(\boldsymbol{u})] = -\nabla^T G(\boldsymbol{u}) \cdot \boldsymbol{u}^* \tag{19A}$$
$$\mathrm{Var}[G_l(\boldsymbol{u})] = |\nabla G(\boldsymbol{u})|^2 \tag{19B}$$

According to Eq. (8), the probability of failure is obtained as follows:

$$P_f \approx P[G_l(\boldsymbol{u}) \leq 0] = \Phi\left(-\frac{\mathrm{E}[G_l(\boldsymbol{u})]}{\sqrt{\mathrm{Var}[G_l(\boldsymbol{u})]}}\right) = \Phi\left(\frac{\nabla^T G(\boldsymbol{u})}{|\nabla G(\boldsymbol{u})|} \cdot \boldsymbol{u}^*\right) = \Phi(-\beta)$$

$$\therefore \beta = -\frac{\nabla^T G(\boldsymbol{u})}{|\nabla G(\boldsymbol{u})|} \cdot \boldsymbol{u}^* \tag{20}$$

Since the position vector of MPP is opposite the gradient vector at MPP according to Eq. (17), the reliability index is formulated as follows:

$$\beta = -\frac{\nabla^T G(\boldsymbol{u})}{|\nabla G(\boldsymbol{u})|} \cdot \boldsymbol{u}^* = \left(-\frac{\nabla^T G(\boldsymbol{u})}{|\nabla G(\boldsymbol{u})|} \cdot \frac{\boldsymbol{u}^*}{|\boldsymbol{u}^*|}\right) \cdot |\boldsymbol{u}^*| = |\boldsymbol{u}^*| \tag{21}$$

Eq. (21) means that the reliability index is equal to the distance between the origin and MPP. Consequently, the reliability index in FORM can be obtained as the distance by solving the optimization problem in Eq. (16). To solve the optimization problem in Eq. (16), an iteration method such as the Rackwitz-Fiessler method are required [5) 7)].

Finally, the principle of FORM is illustrated in Fig. 2. As shown this figure, in FORM, the probability of failure is evaluated by using a one-dimensional standard normal density function having an axis along the gradient vector of limit state function. As shown in the figure, changes in the failure region due to the non-linearity of the limit state function cause approximate error in the probability of failure. However, because the effect on the probability of failure decreases as the distance becomes larger, the degree of this approximate error is regarded as negligible. On the other hand, when the accuracy requirement is higher (error of probability of failure is minimized further), it is preferrable to use an evaluation method that considers the curvature of the limit state function such as the Second Order Reliability Method (SORM), which is introduced in Section 2.3.3.

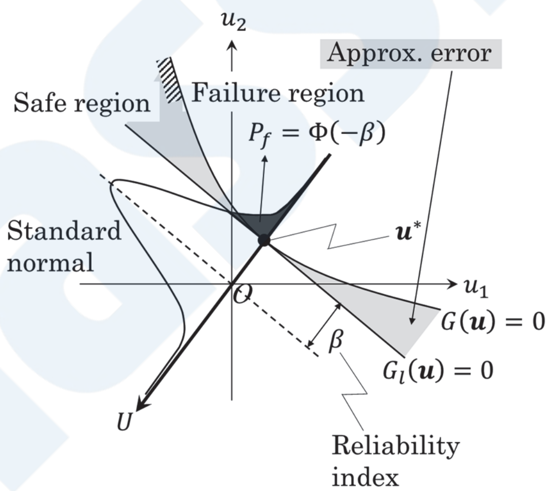

Fig. 2 Principle of FORM

2.3.3 Second Order Reliability Method (SORM)

SORM approximates the limit state function in a second-order Taylor series. Although several methods have been proposed, and the author's work [9)] will be briefly introduced in this paper.

Under the assumption that the random vector $\boldsymbol{x}$ follows an independent normal distribution, the limit state function is approximated by a second-order Taylor series about MPP.

$$g(\boldsymbol{x}) \approx g_s(\boldsymbol{x}) = \boldsymbol{x}^T \boldsymbol{A} \boldsymbol{x} + \boldsymbol{b}^T \boldsymbol{x} + c \tag{22}$$

The limit state function $G_s(\boldsymbol{u})$ mapped by standard normalization of Eq. (22) is formulated as follows:

$$G_s(\boldsymbol{u}) = \boldsymbol{u}^T \boldsymbol{A}' \boldsymbol{u} + \boldsymbol{b}'^T \boldsymbol{u} + c' \tag{23}$$

According to the author's work [9], the probability of failure can be evaluated by dividing the cases depending on whether the sign of the eigenvalue of $\boldsymbol{A}'$ is positive or negative. Details will be omitted here due to their complexity, but the approximate accuracy evaluated by this method is higher than that evaluated by FORM.

2.4 Categories of Uncertainty

In evaluation of the probability of failure, the structural reliability theory supposes that the uncertainty of factors such as stress or strength is represented as a reasonable model. However, uncertainty can be divided into various categories. In structural reliability theory, the following categorization is generally considered [10].

- ✓ Aleatory uncertainty: Essential uncertainty such as physical phenomena, e.g., wave height and material property. Aleatory uncertainty cannot be reduced by collecting knowledge and information.
- ✓ Epistemic uncertainty: Uncertainty due to a lack of information. Epistemic uncertainty can be decreased by technical improvements, e.g., model uncertainty including formulae in rules.

Whereas the uncertainty inherent in a certain type of performance is aleatory uncertainty, epistemic uncertainty is related to the degree to confidence or reliability of the information. While a grasp of aleatory uncertainty allows a statistical understanding of the target phenomenon, an understanding of epistemic uncertainty makes it possible to understand the validity of the statistical model and the sources of uncertainty that should be reduced. An engineering application of the structural reliability theory to structural problems only becomes possible when these uncertainties are quantified. The basic techniques for quantifying uncertainty (i.e., uncertainty quantification) have been organized mathematically in the literature [11].

3. DIFFERENCE OF RELIABILITY DESIGN AND RISK-BASED DESIGN CONSIDERING DESIGN OPTIMIZATION PROBLEM

3.1 Reliability-Based Design Optimization

This section considers reliability-based design and its application to design optimization problems. This approach is called Reliability-Based Design Optimization (RBDO). RBDO searches for the design solution where the desired performance is minimized (or maximized) subject to the constraints of the probability of failure. When the design vector and random vector are represented as $\boldsymbol{d} = (d_1, d_2, \cdots, d_n)^T$ and $\boldsymbol{x} = (x_1, x_2, \cdots, x_{n_r})^T$, respectively, a RBDO problem can be formulated as follows:

$$\text{Min.}: f(\boldsymbol{d}) \tag{24A}$$

$$\text{s.t.}: P\left[g_j(\boldsymbol{d}, \boldsymbol{x}) \leq 0\right] \leq \Phi\left(-\beta_j^{\text{Tar}}\right) \ (j = 1, \cdots, m) \tag{24B}$$

where $f(\cdot)$, m, β_j^{Tar} are an objective function (performance to be minimized, e.g., weight), the number of limit state functions and the target reliability index of the j^{th} limit state function, respectively. The target reliability index provides the upper limit of the probability of failure (a lower limit of reliability or target reliability) for each failure mode and is generally set by the designer.

3.2 Risk-Based Design Optimization

This section considers the application of risk-based design to design optimization problems, which is called risk-based design optimization. The optimal solution is obtained by considering risk, where risk is regarded as objective constraint functions. In this paper, the quantified risk in Eq. (2) is regarded as the expected value of the cost of failure, and an optimization problem to minimize the sum of the expected value of the cost of failure and costs from the other sources C_0 (called initial cost) is considered. This problem can be formulated as follows:

$$\text{Min.}: f(\boldsymbol{d}) = C_0(\boldsymbol{d}) + \sum_{j=1}^{m} C_{Dj}(\boldsymbol{d}, \boldsymbol{x}) \cdot P_{fj} \tag{25A}$$

$$\text{where}: P_{fj} = P\left[g_j(\boldsymbol{d}, \boldsymbol{x}) \leq 0\right] \ \ j = 1, \cdots, m \tag{25B}$$

For simplicity, here, severity C_D is considered to be independent of the design variables, and a single failure mode is considered for simplicity. Under these assumptions, the objective function in Eq. (25) can be reformulated as follows:

$$f'(\boldsymbol{d}) = \alpha \cdot C_0(\boldsymbol{d}) + (1-\alpha) \cdot P_f \quad (26A)$$

$$\text{where: } \alpha = \frac{1}{C_D + 1} \quad (26B)$$

Eq. (26A) is the linear weighted sum of the initial cost and the probability of failure using the weighting factor α. This means that a multi-objective design optimization problem to minimize the initial cost and the probability of failure is solved simultaneously. Eq. (25) can be reformulated as follows:

$$\text{Min.}: C_0(\boldsymbol{d}) \quad (27A)$$

$$\text{Min.}: P_f(\boldsymbol{d}, \boldsymbol{x}) \quad (27B)$$

Optimal solutions of the multi-objective design optimization problem in Eq. (27) are provided as a Pareto front, which is a set of undominated solutions called Pareto solutions. Fig. 3 shows an illustration of Pareto solutions in an objective function space. As shown in this figure, a Pareto solution can be chosen in accordance with the value of the weighting factor α. That is, since the weighting factor α is determined by severity according to Eq. (26B), a Pareto solution can be chosen according to severity.

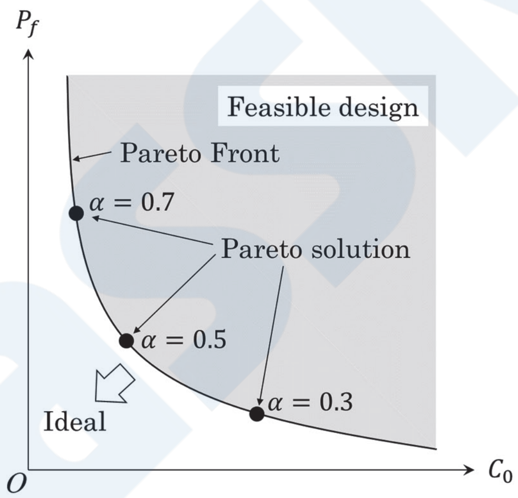

Fig. 3 Pareto solutions of risk-based design optimization

Finally, the interpretation of the Pareto solution in risk-based design will be considered. As an example, Fig. 4 shows the feasible region when the failure probability of the Pareto solution at $\alpha = 0.7$ is set as the upper limit. As shown in this figure, the design that minimizes the initial cost C_0 in the feasible region is the Pareto solution at $\alpha = 0.7$. Thus, the Pareto solution can be interpreted as the result of searching for the solution that minimizes C_0 subject to the limit of the probability of failure. Although this point is essentially the same as in the RBDO in the previous section, the difference between the two is whether the target reliability index is determined by the designer, as in RBDO, or by severity, as in the risk-based design optimization. In other words, the characteristic feature of the risk-based design optimization is that the threshold is determined based on values that are objective and reasonable, namely, severity.

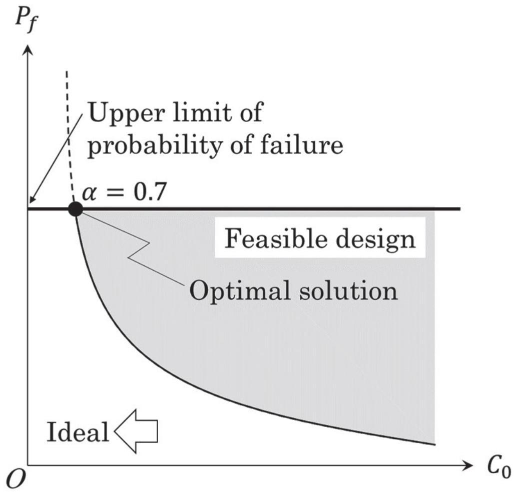

Fig. 4　Interpretation of Pareto solution

4.　APPLICATIONS OF RISK-BASED DESIGN

4.1　GBS-SLA Interim Guideline

In the past, the structural rules for the construction of ships engaged in international voyages were substantially managed by classification societies. However, bulk carrier and oil tanker accidents occurred frequently from the 1980s, which heightened the momentum toward greater involvement of IMO in establishing structural rules for ships. Against this background, IMO MSC77 (Maritime Safety Committee) held in 2003 agreed to establish the GBS, a top-down rule system. Based on this agreement, the IMO began the development of rules, and the IACS also started the development of CSR (Common Structural Rule) in response to the agreement. The CSR conforming to the GBS is generally regarded as an extremely prescriptive rule with a low degree of freedom. Due to these characteristics of the CSR, a different approach has been required to deal with new designs for ships such as new concept ships. Therefore, the need to develop GBS-SLA based on SLA, which sets quantitative safety levels, has been emphasized, and it was agreed that risk should be used as a quantitative index of safety. In addition, the Guidelines for Formal Safety Assessment (FSA) [3],which was issued prior to the discussions on the GBS, was also a focus of attention due to its affinity with SLA. As a result, GBS-SLA was developed referring to many of the approaches in FSA. Table 2 shows the history of moves related to the GBS-SLA.

The GBS-SLA is composed of the following five tiers.

I.　Goals
II.　Functional requirements
III.　Verification of conformity
IV.　Rules and regulations for ships
V.　Industry practices and standards

Among the five tiers, Tiers I and II are included in IMO conventions and Tier IV, which is the detailed technical rules, is included in IMO Codes and the classification society rules. This paper will introduce Tiers I and II.

Goals (Tier I) are high-level objectives which are to be met and should reflect required safety levels. The safety level means the maximum measure of exposure to risk, and should be a level that is acceptable to society. According to the Interim Guideline, the required safety level can be specified explicitly by a quantitative safety level or implicitly by a process to be used for achieving the highest practicable safety level. Goals are established by the Maritime Safety Committee.

Functional requirements (Tier II) provide the criteria to be satisfied in order to meet the goals and are established by IMO in the responsible Committees. Functional requirements should comply with the following conditions:

1. Cover all areas necessary to meet the goal.
2. Address all relevant hazards. Methods for hazard identification as well as their ranking are described in the FSA Guidelines.
3. Provide criteria for verification of the compliance of Tier IV rules.
4. Be independent of specific technologies to allow for further technological development.

5. Clearly describe the functions that should be achieved.

GBS-SLA requires procedures such as identification of hazards and quantification of risks which are defined in the FSA.

Table 2 History of GBS-SLA

Year	IMO	IACS
~1999	Complete loss accidents of large bulk carriers occurred.	
1999	The Erika broke in two and sank of the coast of Brittany, France.	
2001	The FSA Guidelines were approved in MSC74 and MSPC47(2002) as the IMO Rule-Making Process.	
2002	The oil tanker MV Prestige sank off the coast of Galicia, Spain.	
2003	Development of the GBS was agreed at MSC77.	Development of CSR was agreed in the 47th Council, and development began.
2004	Full-scale discussion to establish GBS began from MSC78.	
2005	GBS-SLA was proposed at MSC80.	CSR was adopted in the 52nd Council.
2006		CSR was enacted.
2010	IMO GBS was adopted in MSC87.	
2012	The SLA-based Interim Guideline work plan was endorsed at MSC90, and draft elements to be considered in working groups were agreed.	
2017	Revisions to FSA Guidelines were approved at MSC98 and MPEC72 (2018).	
2018	・Application of the corresponding steps of the FSA Guidelines was discussed at MSC99. ・The draft of the Interim Guideline was approved, and agreement was reached on preparation of the related MSC Circular.	
2019	The Interim Guideline was approved at MSC100.	

4.2 Acceptance Criteria for Fatigue

The principle of risk-based design is that the target reliability is determined based on risk criteria. As one example of structural rule development based on this principle, this section introduces the method for determining the acceptance criteria for fatigue crack damage of hull structures.

Since a hull structure can be regarded as a large-scale welded structure, it contains many welded joints. This means there are multiple evaluation points for fatigue strength in the hull structure. Fatigue strength verification is performed for each of these points using the design S-N diagram. In general, this verification is based on the degree of cumulative fatigue damage D, and is formulated as follows in the Comprehensive Revision of Part C of the ClassNK Rules:

$$\eta \cdot D \leq 1 \tag{28}$$

where η is a correction factor which varies depending on the evaluation point and is determined by whether the point is related to the functionality of the compartment.

For example, let us consider the criteria for fatigue strength using the risk-based design based on Eq. (28). It is assumed that cumulative fatigue damage can be represented by the design vector $\boldsymbol{d}$ and random vector $\boldsymbol{x}$, and the target reliability index for a certain part is β^{Tar}. Then, a constraint using reliability is formulated as follows:

$$P[g(\boldsymbol{d},\boldsymbol{x}) \leq 0] \leq \Phi(-\beta^{\mathrm{Tar}}) \tag{29A}$$

$$\text{where: } g(\boldsymbol{d},\boldsymbol{x}) = 1 - D(\boldsymbol{d},\boldsymbol{x}) \tag{29B}$$

As mentioned in the previous chapter, the left side of Eq. (29A), reliability analysis, is difficult to solve analytically. In addition, repeated reliability analyses for each target part are practically complicated and time-consuming in the practical design process. Considering these points, the Partial Safety Factor (PSF) is often adopted for structural rules and standards from the viewpoint of ease of use by general designers. As a very simple example for understanding the PSF, it is assumed that a constraint equal to Eq. (29A) can be obtained as follows by using the expected value vector $\boldsymbol{\mu}$ and the PSF for fatigue strength η_{PSF}.

$$g_{\mathrm{PSF}}(\boldsymbol{d},\boldsymbol{\mu}) = 1 - \eta_{\mathrm{PSF}} \cdot D(\boldsymbol{d},\boldsymbol{\mu}) \geq 0 \tag{30}$$

where the PSF η_{PSF} is evaluated in accordance with the target reliability index β^{Tar}, and is organized in the form of a partial safety factor table in rules and standards. One method for evaluating the PSF uses the MPP, as mentioned in Chapter 3.

The next problem is how target reliability should be determined. In reliability-based design, designers are allowed to determine the target reliability based on their individual experience. However, when rationality and transparency are required, for example, in ship structural rules, the target reliability should be determined by the risk-based design approach. On the other hand, if the target is fatigue crack failure, the direct effect on the total hull structure is small, but since compartment functions may be lost, it is necessary to consider risk from the viewpoint of maintaining the functions of compartments. In other words, it is necessary to conduct a risk assessment for each member and determine the target reliability corresponding to the risk level as shown in Fig. 5. Use of this concept may also make it possible to identify members that do not require a detailed evaluation.

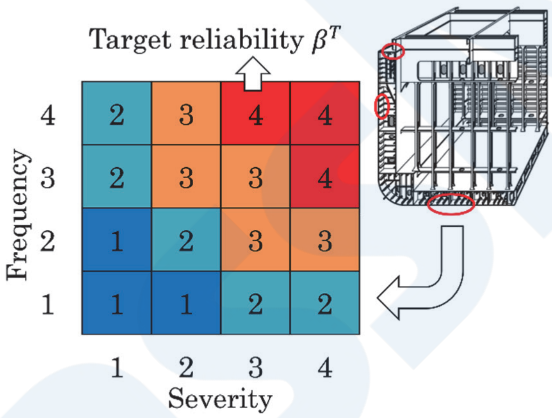

Fig. 5　Risk assessment and determination of the target reliability index for each part

In the concept of risk-based design, the most important task is to create and organize a database. For example, focusing on the watertightness of compartments, it is possible to generalize the data by organizing the degree to which fatigue crack failures that led to loss of watertightness occurred in the past, and recording this information together with related data such as the crack dimensions. Based on this, it is also possible to identify members that lose watertightness easily and the severity of the problem. If necessary, a formula for estimating severity should also be studied.

If this information is arranged in the form of a PSF table, the criteria for fatigue strength using the concept of the risk-based design can be introduced through this process. However, it can be assumed that many technical issues will arise when actually implementing the process described in this paper. The next section discusses those issues and briefly introduces the initiatives of ClassNK in this connection.

4.3　Technical Issues and Initiatives of ClassNK

4.3.1　Collection of Risk Information

As mentioned above, creating a high-quality database is important for using the concept of risk-based design. Focusing on this database, one issue is what items should be used in the classification and recording of accident data. Careful planning and the knowledge of experts are required in order to determine the number of input variables and prerequisites necessary in the severity estimation formula which is constructed after creating the database. Collecting the widest possible range of data and updating the database with appropriate content are also important for maintaining database quality. This will require the development of an environment in which data sharing and reporting are possible in society as a whole.

ClassNK is examining databasing of the information which it acquires through classification surveys and expansion of this to various services. As part of this, we are studying extraction and organization of data specific to risk information and activities to utilize that data in risk assessments and setting of risk criteria. In addition, we are also examining vulnerability reports, which are a framework for obtaining information from a wide range of sources. In this connection, Yamada and Kajita have reported on a framework for collecting and utilizing risk-specific information in the entire maritime cluster in this issue of ClassNK Technical Journal.

4.3.2 Uncertainty Quantification

Uncertainty quantification is important since risk-based design is based on the concept of the structural reliability theory. In particular, in the design of a hull structure, it must be remembered that the uncertainty of the stresses affecting a ship varies greatly depending on the route and weather conditions. Epistemic uncertainty is reduced by utilizing data, and a highly accurate analysis that is closer to reality can be expected.

ClassNK has studied the following topics as research for establishing highly accurate analysis and evaluation techniques.

- ✓ Research to identify the oceanographic conditions that ships encounter when navigating in actuals seas with high accuracy by using Automatic Identification System (AIS) data, and quantitative assessment of the effect of maneuvering.
- ✓ Research to reduce wave height error caused by tidal currents.
- ✓ Research on equations for estimating collapse strength after elastic buckling with high accuracy based on a physically meaningful background.

ClassNK also conducts daily activities to expand this research to the development of risk-based structural rules based on these activities.

5. CONCLUSION

This paper introduced the structural reliability theory, which is the basis of risk-based design, and discussed the difference between reliability-based and risk-based design by using a design optimization problem. As further developments of risk-based design, after touching on GBS-SLA, which is a guideline for the development of structural rules, an example of the development of acceptance criteria for fatigue using the concept of risk-based design and related technical issues were also discussed. The author hopes this paper will be of assistance for incorporation in risk-based design.

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