Reliability analysis of lashing bridge of ultra-large container ship based on improved gradient boosting decision tree–Monte Carlo method

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Abstract: [Objectives] For the structure of the lashing bridge of an ultra-large container ship, the complicated design and severe load environments lead to higher requirements for reliability. Aiming at the problems of the poor efficiency and low accuracy of large ship structure reliability analysis, this paper proposes an improved gradient boosting decision tree–Monte Carlo (GBDT–MC) method. [Methods] First, an approximate model of the improved gradient boosting decision tree (GBDT) is established through the Python library, fewer sample points are generated through experiment design and the sample points near the failure surface are screened. The SMOTE algorithm is then used to synthesize new sample points and participate in finite element calculation, as well as being combined with the original sample points to form a training set. The trained approximate model is used to predict the sample point information generated by the Monte Carlo (MC) method, thereby completing the structural reliability analysis. Finally, the feasibility and accuracy of the improved GBDT–MC method is verified by two examples and applied to the reliability analysis of the structure of the lashing bridge of an ultra-large container ship. [Results] The calculation results show that the failure probability error under the effect of static lashing force is 3.5% and the calculation time of the improved GBDT–MC method is 2.55 h, but the MC method requires 416.7 h. Therefore, within the allowable calculation error range, the improved GBDT–MC method can greatly reduce the calculation time of reliability analysis. [Conclusions] This improved GBDT–MC method significantly improves calculation accuracy and shortens the calculation time, which can provide support for the optimization design of high reliability index structures.

Key words: lashing bridge; reliability analysis; SMOTE algorithm; gradient boosting decision tree (GBDT); Monte Carlo method

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0 Introduction

Compared with the lashing bridges of large container ships, those of ultra-large container ships are of higher and wider structures. Moreover, lashing points are distributed in the planes of different heights of these lashing bridges. As a result, the overall stiffness of these lashing bridges is relatively low. In the structural analysis of lashing bridges of ultra-large container ships, Zeng et al. [1] summarized the high stress zones under extreme working conditions by numerically simulating lashing bridges and proposed corresponding suggestions about structural optimization. Wang [2] analyzed the vibration re-
response of lashing bridges based on numerical modeling and put forward the modifications to some structures failing to meet regulatory requirements. However, there are few research results on structural reliability analysis of lashing bridges of ultra-large container ships. This is because relevant functions cannot be explicitly expressed. Thus, it is difficult to directly obtain reliability indexes and failure probabilities through the first-order second moment (FOSM) or the second-order reliability method (SORM). However, the Monte Carlo (MC) method can be used for calculation. In the MC method, failure probabilities can be expressed by the frequency of sample points of failure probability occurring among all sample points, but this yields very high overall calculation costs but low calculation efficiency.

In order to solve this problem, we can adopt two methods. One is to reduce the total number of samples by variance reduction techniques, such as importance sampling (IS). However, this method requires tens of thousands of sample points. The other is to reduce the calculation time of individual sample points by model approximation techniques. Schuermans et al. [3] established an adaptive response–surface surrogate model by directional sampling, thus improving the MC method. In addition, they compared the advantages and disadvantages of using low–order polynomial functions, spline functions, and neural networks to expand response surfaces for reliability analysis. On this basis, they found that spline functions and neural networks could more accurately handle reliability analysis of high–dimensional complex structures. Kang et al. [4] improved the MC method by response surface methodology (RSM) based on moving least squares methods. This method identifies failure zones and most probable points (MPPs) through stepwise approximation by increasing the weight coefficients of sample points near failure surfaces, thus reducing calculation costs. Echard et al. [5] combined an improved Kriging approximation model with the MC method. Then, through active learning, the sample points updated in each iteration of the adaptive Kriging model were all located near a failure surface. In this way, high approximation of the function of the failure surface was achieved. Therefore, this method is of good adaptability to high–reliability models. Yu et al. [6] and Wang [7] conducted structural reliability analysis by taking response surfaces as approximation models. Zhang [8] and Huang et al. [9] completed calculation of structural reliability indexes and failure probabilities by Kriging based approximation models. Chen et al. [10] and Meng et al. [11] calculated structural reliability by combining neural networks with the MC method. Blagus et al. [12] synthesized a new machine–learning algorithm, namely a SMOTE algorithm, by "oversampling" a few sample points. The use of surrogate models to analyze structures of high–reliability indexes will result in such problems as many samples, low proportions of failure samples, and poor fitting accuracy. By contrast, the SMOTE algorithm can solve the over–fitting caused by increasing minority–class samples through simple sample copying in traditional oversampling algorithms. Thus, it can improve the fitting accuracy of failure surfaces.

In this paper, the SMOTE algorithm was used to increase the number of minority–class sample points near a failure surface. Then, an approximation model based on a gradient boosting decision tree (GBDT) was trained. On this basis, in combined with the MC method, this paper completed calculation of structural reliability, providing a reference to structural optimization.

1 Improved GBDT–MC method

1.1 GBDT method

The GBDT method is an iterative decision–tree algorithm [13]. It is assumed that there are \( m \) training samples: 
\[
\{(X^{(1)}, y^{(1)}), (X^{(2)}, y^{(2)}), \ldots, (X^{(i)}, y^{(i)}), \ldots, (X^{(m)}, y^{(m)})\}
\]  
(1)

where \( X^{(i)} = \{x_{1}^{(i)}, x_{2}^{(i)}, \ldots, x_{p}^{(i)}, \ldots, x_{n}^{(i)}\} \) is the \( i \)-th sample, \( i=1, 2, \ldots, m \); specifically, \( x_{j}^{(i)} \) is the \( j \)-th dimensional feature of the \( i \)-th sample, \( j = 1, 2, \ldots, n \); \( y^{(i)} \) is the label of the \( i \)-th sample, and the label of a sample for regression is a continuous value.

Essentially, a training model is to realize mapping from sample features \( X^{(i)} \) to sample labels \( y^{(i)} \). Its mapping function \( F(X) \) is given by
\[
F(X) = X^{(i)} \rightarrow y^{(i)}
\]  
(2)

For the solving of the mapping function \( F(X) \), a loss function \( L(y, F(X)) \) is usually set to the training model, where \( y \) is a set of sample labels. The loss function can be expressed in the form of square loss, absolute loss, Huber loss, or quantile loss. Specifically, the most common square loss function is as follows.
\[
L(y, F(X)) = (y - F(X))^2
\]  
(3)

The optimal mapping function \( F \) can be obtained
when the loss function is minimized, namely
\[ F^* = \underset{F(X)}{\text{arg min}} L(y, F(X)) \]  (4)

For a linear regression problem, its mapping function \( F(X; W) \) is as follows.
\[ F(X; W) = WX = w_0 + w_1x_1 + w_2x_2 + \cdots + w_nx_n \]  (5)
where \( X \) is a set of sample features; \( W \) is a set of mapping parameters; \( w_0, w_1, \ldots, w_n \) are features of the set \( X \); \( x_1, x_2, \ldots, x_n \) are mapping parameters of the features \( x_1, x_2, \ldots, x_n \).

In essential, the optimal solution to the mapping function \( F(X; W) \) is to calculate a mapping parameter \( W \). The simplest and most direct solving method is the gradient descent method, namely
\[ \min f(W) \]  (6)
where \( f(W) \) is an objective function.

The basic idea of the gradient descent is to first select an initial point \( W^0 \) and then update it repeatedly, which can be expressed by
\[ W^{t+1} = W^t + p' \cdot d^t \]  (7)
where \( W^{t-1} \) and \( W^t \) are the \((t+1)\)-th and \( t\)-th iteration results of the parameter \( W \), respectively, and the number of iterations is \( t = 0, 1, \ldots, T \). \( p' \) is a step size; \( d^t = \frac{\partial}{\partial W} f(W)|_{W^t} \) refers to a gradient descending direction.

Suppose that the optimal solution to \( f(W) \) is \( W^* \), which is obtained from \( T \) iterations of the initial value \( W^0 \). Let \( W^0 = d^0 \), and then
\[ W^* = \sum_{t=0}^{T} p^t \cdot d^t \]  (8)

In general function space, the optimal mapping function \( F^*(X) \) can be obtained according to Eq. (8):
\[ F^*(X) = \sum_{t=0}^{T} f_t(X) \]  (9)
where \( f_t(X) = -p^t g_m(X) \). Specifically, \( g_m(X) = \left[ \frac{\partial L(y, F(X))}{\partial F(X)} \right] \).

As \( f_t(X) = -p^t g_m(X) \), it is assumed that the set \( f(X) \) of \( f(X) \) is determined by the parameter \( a \). Then
\[ f(X) = -p \cdot h(X; a) \]  (10)
where \( p \) is a set of step sizes; \( h(X; a) = x_0 + a(X - x_0) \), in which \( x_0 \) is a constant term and \( a = \arg\min_{a} \sum_{t=0}^{T} [y - p \cdot h(X; a)]^2 \).

Boosting is an important method of ensemble learning \[ [14] \]. In this method, different training-sample sets are obtained by re-sampling training samples. Then, weak learners are trained over these new training-sample sets, respectively. Finally, the results of all weak learners are merged and taken as the result of the final strong learner. Initially, the weight of various samples is equal. First of all, the first weak learner learns training samples. After the learning is completed, the weight of wrong samples is increased and meanwhile that of correct samples is decreased. Then, the second weak learner learns the samples with new weights. This continues successively until the \( b \)-th weak learner completes its learning. Finally, the results of \( b \) weak learners are merged to obtain a strong learner. Noteworthily, there is a sequence among these learners, and the weight of each learner is different. Fig. 1 shows the detailed principle.

In Fig. 1, the final prediction result is to merge \( b \) weak learners, thus producing a strong learner \( f(X) \):
\[ f(X) = \sum_{i=1}^{b} \theta_i \varphi_i(X) \]  (11)
where \( \theta_i \) is a weighting parameter, \( i = 1, 2, \ldots, b \); \( \varphi_i(X) \) is the prediction result of the \( v \)-th weak learner.

According to Eq. (10), it is found that Eq. (11) shows a gradient solving process. This process is called gradient boosting (GB), also known as the framework of a gradient-based Boost method. A decision tree in GBDT is a regression tree in the method of classification and regression trees (CART). At the initial time, CART only contains a root node, so \( m \) samples are all distributed at the root node. In this case, \( m \) times of the sample variance \( \hat{s}^2 \) of the root node is as follows.
\[ \hat{s}^2 \cdot m = (y^{(1)} - \bar{y})^2 + (y^{(2)} - \bar{y})^2 + \cdots + (y^{(m)} - \bar{y})^2 \]  (12)
where \( \bar{y} \) is the label mean of \( m \) training samples.

At this time, the \( i \)-th sample is selected from \( m \) samples and the \( j \)-th dimensional feature is selected from \( n \)-dimensional features, namely \( x_i^{(j)} \) as the splitting criterion. When the \( j \)-th dimensional feature of
the \( i \)-th sample, \( X^{(i)} \), is less than or equal to the splitting criterion \( X_j^{(0)} \), the sample \( X^{(i)} \) is classified into the left subtree; otherwise, it is classified into the right subtree. Through the above operations, provided that number of the samples classified into the left subtree is \( m_l \), we can find that number of the samples classified into the right subtree is \( m_r = m - m_l \).

The optimal splitting result is the minimum sum of variances of left and right subtrees, namely

\[
\min(s_1^2 + m_1 s_2^2) = \min \left( \sum_{X^{(i)} \in \text{left}} (y^{(i)} - \bar{y}_1)^2 + \sum_{X^{(i)} \in \text{right}} (y^{(i)} - \bar{y}_2)^2 \right)
\]

(13)

where \( s_1^2 \) and \( s_2^2 \) are the sample variances of left and right subtrees, respectively; \( \bar{y}_1 \) and \( \bar{y}_2 \) are the label means of nodes at left and right subtrees, respectively. Splitting continues successively by taking \( \min(s_1^2 + m_1 s_2^2) \) as the criterion until the final splitting result is obtained.

In conclusion, GBDT uses the regression trees in CART as weak learners and conducts iterations with a gradient descent algorithm under the framework of gradient boosting. In addition, it produces multiple weak learners by splitting based on the principle of minimizing loss functions and strong learners by combining weak learners of different weights. This process is repeated continually until regression is achieved.

1.2 SMOTE algorithm

The SMOTE algorithm is an oversampling method for synthesizing minority–class data. Its basic idea is to artificially synthesize new samples by analyzing minority–class samples and then add the new samples to the data set. Its specific process is as follows: first, for each sample \( X^{(i)} \) in a random minority–class sample set \( \{ X^{(i)} | i = 1, \cdots, m \} \), its Euclidean distances to all the other samples in the set \( \{ X^{(i)} | i = 1, \cdots, m \} \) are calculated to obtain a \( k \)-nearest neighbor model. Then, it is supposed that the up-sampling rate is \( N \), and \( U \) nearest neighbors \( X_{(i)} | u = \{ 1, \cdots, U \} \) are selected randomly among the \( k \) nearest neighbors. Finally, linear interpolation is conducted between \( \{ X^{(i)} | i = 1, \cdots, m \} \) and \( \{ X_{(i)} | u = \{ 1, \cdots, U \} \} \) to produce a new sample point \( X^{(\text{new})} \):

\[
X^{(\text{new})} = X^{(i)} + \text{rand}(0, 1) \times \left( X_{(i)} - X^{(i)} \right)
\]

(14)

where \( \text{rand}(0, 1) \) is a natural number generated randomly.

\( m \) new sample points can be synthesized by repeating the above steps for \( m \) times. A new training set can be generated by combining the new sample points with the original ones.

1.3 Principle of improved GBDT–MC method

In view of structural reliability analysis, the MC method will test whether sample points are in a failure zone or not by generating a large number of points (10^6–10^7 orders of magnitude). According to Bernoulli’s law of large numbers, there is

\[
\lim_{m \to \infty} P\left( \frac{|\mu_m - \mu_0|}{\sigma_0} < \varepsilon \right) = 1
\]

(15)

where \( P \) is a probability function; \( \mu_m \) is number of failure points in structural reliability analysis. When the number \( m \) of sample points is large enough, a structural failure probability can be expressed as the number \( \mu_m \) of failure points divided by the number \( m \) of sample points. However, for a complex engineering structure, it is extremely time-consuming to calculate the information of all sample points by a finite element method. Thus, this is not feasible. \( \mu_m \) is a probability of sample failure; \( \varepsilon > 0 \), which is a randomly given real number.

In conclusion, the principle of the improved GBDT–MC method proposed in this paper is as follows: first, a finite–element method is adopted to calculate the information of a few sample points, and sample points near a failure surface are screened. Then, the SMOTE algorithm is used to synthesize new sample points to participate in the finite element calculation. Thus, a training set is formed by combining the new sample points with original ones. Finally, the GBDT approximation model is trained, and the trained approximation model is adopted to predict the information of sample points in the MC method. In this way, structural reliability analysis can be completed, and calculation accuracy and efficiency can be significantly improved.

1.4 Iterative process of improved GBDT–MC method

1) Design experiments in design space: obtain an original sample set \( X_i \) by uniform sampling, and its response set \( G(X_i) \) through finite element calculation of structural performance function values.

2) Screen some sample points near a failure surface under the screening criterion of the distance between the response value of a sample point and the constrained boundary; synthesize a new sample set...
$X_i$ by the SMOTE algorithm and obtain its response set $G(X_i^2)$ based on finite element calculation; combine the original sample set and its response set with the sets obtained by the SMOTE algorithm to obtain a new sample set $X_i$ and response set $G(X_i)$.

3) Construct a GBDT model: establish a GBDT training model by taking the sample set $X_i$ as input and the response set $G(X_i)$ as output.

4) Verify model accuracy: adjust model parameters by Python library functions and conduct cross verification by dividing the training set into a test set and a verification set; then, evaluate the root-mean-square errors of the GBDT training model.

5) Predict response values and calculate failure probabilities. For the GBDT model that meets evaluation requirements, MC sample points are input to the prediction function of the model. If $G(X_i) < 0$, it is indicated that the structure has failed with $n_G$ failure points. Then, the failure probability $P_f$ and reliability index $\beta$ of the structure are as follows.

\[
P_f = \frac{n_G}{n_{MC}}
\]

\[
\beta = \Phi^{-1}(1 - P_f)
\]

where $n_{MC}$ is the number of the total samples produced by the MC method; the function $\Phi$ is a standard normal cumulative distribution function.

Fig. 2 shows the flow chart of the improved GBDT-MC method.

### 2 Verification of applicability of improved GBDT-MC method

In view of number of sample points, failure probabilities, and reliability indexes $\beta$, this paper will verify accuracy and stability of the improved GBDT-MC method in structural reliability analysis in combination with References [5,15].

#### 2.1 Example 1: a failure surface with an analytical expression

The example is about the reliability analysis of mechanical performance of a nonlinear oscillator. Fig. 3 shows its structure. Its ultimate state equation $g(c_1, c_2, M, r, t_1, F_1)$ is as follows.

\[
g(c_1, c_2, M, r, t_1, F_1) = 3r - |z_{\text{max}}| = 3r - \frac{2F_1}{Mh_0 \sin(h_0t_1/2)}
\]

where $c_1$ and $c_2$ refer to the stiffness of springs; $M$ is the mass of a trolley; $r$ is a displacement limit of the trolley; $t_1$ is action time of force; $F_1$ is acting force; $z_{\text{max}}$ is the maximum displacement of the trolley; $h_0 = \sqrt{(c_1 + c_2)/M}$.

Table 1 shows distribution types and distribution parameters of six random variables, $c_1$, $c_2$, $M$, $r$, $t_1$ and $F_1$, in this example. For this problem, Echard et al. [5] used an improved neural network model in combination with the MC method (back propagation–Monte Carlo, BP–MC) for calculation. In this paper, the improved GBDT–MC model will be trained with the same number of samples as that in Reference [5]. Table 2 lists relevant comparison results.

<table>
<thead>
<tr>
<th>Stochastic variable</th>
<th>Distribution</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$c_1$</td>
<td>Normal</td>
<td>1.0</td>
<td>0.10</td>
</tr>
<tr>
<td>$c_2$</td>
<td>Normal</td>
<td>0.1</td>
<td>0.01</td>
</tr>
<tr>
<td>$M$</td>
<td>Normal</td>
<td>1.0</td>
<td>0.05</td>
</tr>
<tr>
<td>$r$</td>
<td>Normal</td>
<td>0.5</td>
<td>0.05</td>
</tr>
<tr>
<td>$t_1$</td>
<td>Normal</td>
<td>1.0</td>
<td>0.20</td>
</tr>
<tr>
<td>$F_1$</td>
<td>Normal</td>
<td>1.0</td>
<td>0.20</td>
</tr>
</tbody>
</table>
Firstly, a finite element model of the failure surface was established. The MC method was used to produce \(1 \times 10^7\) sample points, and the number of failure sample points was calculated by Eq. (17). Then, the failure probability and reliability index of the structure were calculated by Eq. (16), and relevant results are shown in Table 2.

In Reference [5], the BP-MC method produced 1281 sample points by direct sampling and then obtained a response set through calculation. In this paper, 881 sample points were generated by uniform sampling, and a preliminary response set was obtained through calculation. In addition, 100 sample points near the failure surface were obtained by screening. Then, in combination with the SMOTE algorithm, the sub-sample set was expanded by four times, and a new response set of 400 sample points was obtained. On this basis, a training set was obtained in combination with the original response set. From the comparison in Table 2, it is found that in the case of training with the same number of sample points, the improved GBDT-MC method yields higher accuracy than the BP-MC method.

### 2.2 Example 2: ten-bar truss structure

In this example, the failure surface is an implicit ten-bar truss structure, as shown in Fig. 4. Nodes 1 and 4 are simply supported, and both nodes 5 and 6 are subjected to vertically-downward concentrated force (444.822 kN). The cross-sectional area of each member, \(S_d\) (where \(d = 1, 2, \ldots, 10\)), is taken as a random variable. Specifically, \(S_d \sim N(64.52, 1.27^2)\), which means the cross-sectional area \(S_d\) obeys the normal distribution with a mean of 64.52 cm\(^2\) and variance of 1.27\(^2\). Suppose that allowable stress of the structure is 165 MPa, then the performance function \(g(S)\) of the structure is as follows.

\[
g(S) = 165 - |\sigma(S)|_{\text{max}} \tag{18}\]

where the set of cross-sectional areas is \(S = \{S_1, S_2, \ldots, S_{10}\}\); \(|\sigma(S)|_{\text{max}}\) is the maximum of absolute values of structural stress.

For this problem, Wei et al. [15] improved the response-surface method by a moving least square method (MLSM), who established a dynamic response surface model in combination with the first-order second-moment method. This paper trained the improved GBDT-MC model with the same number of samples as that in Reference [15]. Table 3 lists relevant comparison results.

### Table 3 Comparison of calculation results of different methods (Example 2)

<table>
<thead>
<tr>
<th>Method</th>
<th>Number of samples</th>
<th>Reliability index (\beta)</th>
<th>Failure probability (P_f)</th>
<th>Failure probability error/%</th>
</tr>
</thead>
<tbody>
<tr>
<td>MC</td>
<td>(1 \times 10^6)</td>
<td>3.182</td>
<td>7.30 \times 10^4</td>
<td>-</td>
</tr>
<tr>
<td>MLSM([15])</td>
<td>105</td>
<td>3.166</td>
<td>7.72 \times 10^4</td>
<td>5.75</td>
</tr>
<tr>
<td>Improved GBDT-MC</td>
<td>105</td>
<td>3.188</td>
<td>7.14 \times 10^4</td>
<td>2.19</td>
</tr>
</tbody>
</table>

Firstly, a finite element model of the truss structure was established. The MC method was used to produce \(1 \times 10^6\) sample points, and the stress states of all the sample points were obtained based on finite element analysis. The number of failure sample points was calculated by Eq. (18). Then, the failure probability and reliability index of the structure were obtained by Eq. (16). Table 3 lists relevant results.

In Reference [15], the MLSM method was adopted for iteration for five times, and at least 21 sample points near the center point needed to be involved in each iteration, thus totaling 105 sample points. In this paper, 65 sample points were produced by uniform sampling, and a preliminary response set was obtained through calculation. In addition, 10 sample points near the failure surface were obtained by screening. Then, in combination with the SMOTE algorithm, the sub-sample set was expanded by four times, and a new response set of 40 sample points was obtained. On this basis, a training set was obtained in combination with the original response set. From the comparison in Table 3, it is found that in the case of training with the same number of sample points, the improved GBDT-MC method yields higher accuracy than the MLSM method.
3 Reliability analysis of lashing bridges of ultra-large container ships based on improved GBDT–MC method

The object of structural reliability analysis in this paper is the 07# lashing bridge of a 20 000 TEU ultra-large container ship, as shown in Fig. 5. The thicknesses of plates of the lashing bridge were selected as design variables, and various design variables obey normal distribution. A total of 14 design variables \(l_1-l_{14}\) were selected. Specifically, the dimensions of the frame and columns were known. The mean values of various variables were from measured data, and standard deviations were assumed to be 10% of the mean values. Table 4 lists the specific information. As to boundary conditions, the bottom was clamped, and static lashing force was 175 kN. This meets the code of China Classification Society [16].

**Fig. 5 Lashing bridge of 20 000 TEU ultra large container ship**

**Table 4 Design variables of the lashing bridge**

<table>
<thead>
<tr>
<th>No.</th>
<th>Name</th>
<th>Mean/mm</th>
<th>Standard deviation/mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>l_1</td>
<td>First-tier sideboard</td>
<td>8</td>
<td>0.8</td>
</tr>
<tr>
<td>l_2</td>
<td>Support plate</td>
<td>15</td>
<td>1.5</td>
</tr>
<tr>
<td>l_3</td>
<td>Second-tier platform</td>
<td>6</td>
<td>0.6</td>
</tr>
<tr>
<td>l_4</td>
<td>Third-tier platform</td>
<td>6</td>
<td>0.6</td>
</tr>
<tr>
<td>l_5</td>
<td>Third-tier sideboard</td>
<td>12</td>
<td>1.2</td>
</tr>
<tr>
<td>l_6</td>
<td>Fourth-tier platform</td>
<td>6</td>
<td>0.6</td>
</tr>
<tr>
<td>l_7</td>
<td>Fourth-tier sideboard</td>
<td>15</td>
<td>1.5</td>
</tr>
<tr>
<td>l_8</td>
<td>Fifth-tier sideboard</td>
<td>20</td>
<td>2</td>
</tr>
<tr>
<td>l_9</td>
<td>Fifth-tier platform</td>
<td>15</td>
<td>1.5</td>
</tr>
<tr>
<td>l_{10}</td>
<td>Central shear wall</td>
<td>12</td>
<td>1.2</td>
</tr>
<tr>
<td>l_{11}</td>
<td>Side shear wall</td>
<td>8</td>
<td>0.8</td>
</tr>
<tr>
<td>l_{12}</td>
<td>Bottom bracket</td>
<td>20</td>
<td>2</td>
</tr>
<tr>
<td>l_{13}</td>
<td>Third-tier bracket</td>
<td>20</td>
<td>2</td>
</tr>
<tr>
<td>l_{14}</td>
<td>Fourth-tier bracket</td>
<td>12</td>
<td>1.2</td>
</tr>
</tbody>
</table>

According to the standard [16], the allowable composite stress of a lashing bridge should not be more than 0.88 times the yield limit of plates. In Fig. 5, the main structure of the lashing bridge is built with AH36 high-strength steel, with its yield limit of 355 MPa. Then, the performance function \(g(l)\) of the structure is as follows.

\[
g(l) = 312.4 - |σ(l)|_{von}
\]  

(19)

where the set of sheet thickness is \(l = \{l_1, l_2, \cdots, l_{14}\}; |σ(l)|_{von}\) is composite stress of the structure.

In view of the lashing bridge shown in Fig. 5, structural reliability analysis was carried out by the MC method and the improved GBDT–MC method, respectively. Table 5 shows the comparison of calculation results.

**Table 5 Comparison of calculation results**

<table>
<thead>
<tr>
<th>Method</th>
<th>Number of samples</th>
<th>Calculation time/h</th>
<th>Reliability index (\beta)</th>
<th>Failure probability (P_f)</th>
<th>Failure probability error/%</th>
</tr>
</thead>
<tbody>
<tr>
<td>MC</td>
<td>(5\times10^4)</td>
<td>416.7</td>
<td>3.540</td>
<td>(2.0\times10^{-4})</td>
<td>-</td>
</tr>
<tr>
<td>Improved GBDT-MC</td>
<td>300</td>
<td>2.55</td>
<td>3.550</td>
<td>(1.93\times10^{-4})</td>
<td>3.5</td>
</tr>
</tbody>
</table>

Firstly, a finite element model of the lashing bridge was established. The MC method was used to produce \(5\times10^4\) sample points, and the stress states of all the sample points were obtained based on finite element analysis. The number of failure sample points was obtained by Eq. (19). Then, the failure probability and reliability index of the lashing bridge were obtained by Eq. (16). Table 5 lists relevant results.

According to the calculation results in Table 5, the lashing bridge of an ultra-large container ship under static lashing force has the failure probability that can reach an order of magnitude of \(10^{-4}\), possessing high reliability. This is because the structure is made of high-strength steel. In addition, with the consideration of such uncertainties as environmental load, construction process, and human operation in engineering practice, a higher requirement for the safety margin is given to the structure.

In this paper, 220 sample points were produced by uniform sampling, and a preliminary response set was obtained through calculation. In addition, 20 sample points near the failure surface were obtained by screening. Then, in combination with the SMOTE algorithm, the sub-sample set was expanded by four times, and a new response set of 80 sample points was obtained. Thus, a training set was obtained by calling a total of 300 finite element calculations. From the comparison in Table 5, the improved GBDT–MC method has an error in failure probability at 3.5%, with duration as 2.55 h, while the MC method
spends 416.7 h. Therefore, within an allowable range of calculation errors, the improved GBDT–MC method can greatly reduce the calculation time of reliability analysis.

4 Conclusions

In order to solve large time consumption of single calculation in reliability analysis of complex structures, an improved GBDT–MC method was proposed in this paper to calculate failure probabilities. In this method, a GBDT approximation model was established through the Python library, and a few sample points were generated experimentally. In addition, the number of sample points near a failure surface was increased through the SMOTE algorithm. On this basis, a training set was obtained in combination with original sample points. Then, the prediction of the samples produced by the MC method was completed by training the approximation model, so as to finally complete the calculation of failure probabilities. Moreover, the applicability of the improved GBDT–MC method was verified based on two examples, and the method was applied to the reliability analysis of a lashing bridge of an ultra–large container ship. Conclusions are as follows.

1) The improved GBDT–MC method proposed in this paper is suitable for structural reliability analysis, especially for structures with a high reliability index.

2) The interpolation of samples near a failure surface by the SMOTE algorithm can increase the proportion of minority-class samples and effectively decrease total sampling frequency, thus reducing calculation time.

3) The improved GBDT–MC method can realize highly–approximate fitting of a failure surface, thus greatly improving calculation accuracy.

It should be pointed out that with the increase in the number of sample points in the training set, the calculation accuracy of the improved GBDT–MC method will be improved accordingly. In addition, the information of the sample points participating in each training can be saved in the model and then efficiently integrated with the optimization algorithm to provide support for follow–up reliability optimization.

References


基于改进梯度提升决策树—蒙特卡罗法的超大型集装箱船绑扎桥梁可靠性分析

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摘 要：对超大型集装箱船绑扎桥梁结构而言，复杂的设计结构和恶劣的载荷环境对其可靠性提出了更高的要求。针对大型船舶结构可靠性分析时计算效率低、计算精度差等问题，提出基于改进梯度提升决策树—蒙特卡罗（GBDT-MC）方法。

方法：首先，通过Python库建立改进梯度提升决策树（GBDT）的近似模型，根据实验生成较少的样本点，并筛选位于失效面附近的样本点；接着，运用SMOTE算法合成新的样本点并参与有限元计算，进而结合原有的样本点形成训练集；然后，采用已训练的近似模型预测蒙特卡罗（MC）方法所产生的样本点信息，完成结构的可靠性分析；最后，运用算例验证改进GBDT-MC方法的可行性和准确性，并将其应用于超大型集装箱船绑扎桥梁结构的可靠性分析。

结果：计算结果表明：案例中超大型集装箱船绑扎桥梁结构在静态绑扎力作用下的失效概率误差为3.5%，改进GBDT-MC方法的计算耗时为2.55 h，而MC方法则需要416.7 h，可见在允许的计算误差范围内，改进GBDT-MC方法可以大为缩减可靠性分析的计算时间。

结论：改进GBDT-MC方法能显著提高计算精度并缩短计算时间，可为结构可靠性的优化设计提供支持。

关键词：绑扎桥；可靠性分析；SMOTE算法；梯度提升决策树；蒙特卡罗方法

计及流体影响的船舶回转冰阻力数值模拟

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摘 要：极地船舶在极地航行时，复杂的冰阻力不仅会给船舶带来结构上的威胁，还会对船舶的操纵性提出了新的挑战。研究中主要集中在船—冰碰撞的强相互作用上，而很少有研究流体对冰阻力的影响。采用非线性有限元方法，基于适当的冰材料模型和合理的耦合破坏模式，研究船舶回转运动过程中冰与船之间复杂、强烈的非线性相互作用。同时，采用流固耦合方法，研究流体对舰—冰相互作用的影响。数值结果与经验公式的对比确定了模拟的有效性与可靠性，其中对治有、无流体作用时船舶受到的纵向、横向和垂向冰阻力情况显示，计及流体影响时，船舶的冰阻力在3个自由度上会有明显提升。计及流体影响的船舶回转运动中考虑流体对冰阻力的影响，能准确预测船舶回转时的冰阻力且能有效保证船舶的航行安全。

关键词：海冰；阻力；数值模拟；流固耦合；有限元法