

Structural Deformation Prediction of Underwater Exploded Ship Hull Girder Using Machine Learning

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Abstract

Near-field underwater explosions can cause substantial damage to offshore ship structures, presenting considerable risks to their integrity. This study focused on rapidly predicting girder structure deformation in ship hulls subjected to near-field explosions from small equivalent-weight spherical charges underwater. The Runge–Kutta discontinuous Galerkin method (RKDG) was employed to calculate the explosive load generated by the spherical charge. This load was then applied to the nonlinear finite element solver software, ABAQUS, to determine the maximum deformation of the ship hull girder structure under the impulse load. By comparing the results with experimental data, the accuracy of the proposed model was validated, confirming that the RKDG finite element coupling calculation effectively simulates the response characteristics of spherical charges in near-field explosion scenarios. Subsequently, two machine learning algorithms driven by data, namely extreme gradient boosting (XGBoost) and random forest (RF), were employed to dynamically predict the maximum girder structure deformation in ship hulls. The analysis demonstrated that both models successfully predicted the maximum deformation. The root mean square error for the XGBoost model (27.67) was lower than that of the RF model (50.31). The XGBoost model also fitted 96% of the training data, compared to 94% for the RF model. Moreover, the relative error of the XGBoost model (6.25%) was lower than that of the RF model (10.38%). Overall, XGBoost is highly suitable for predicting girder structure deformation in ship hulls subjected to underwater explosions.

Keywords Underwater explosion; Hull girder; Damage prediction; Discontinuous galerkin; Machine learning

1 Introduction

Modern torpedoes and other underwater weapons primarily cause damage and destruction to vessels, aircraft carriers, and other ships through near-field explosions (Gao et al., 2020; Wang et al., 2020b). The blast waves generated by these underwater explosions and contact detonations impose a series of highly nonlinear challenges to the structures of vessels and carriers (Cole, 1948; Rajendran and Nar-

asimhan, 2001). These explosive loads result in various structural malfunctions, including deformation, depression, and even localized ruptures. Over the past several decades, numerous scholars have investigated these complex nonlinear phenomena in ship hull structures subjected to underwater explosions.

The discontinuous nature of the blast wave from an underwater explosion, with pressures occasionally exceeding 1 GPa, causes rapid movement in the surrounding fluid. Extensive research has been conducted on the characteristics and impacts of blast waves. Lin et al. (2021) investigated the overlapping pressure effects of stress waves from multipoint underwater explosions and studied the damage patterns of circular plates under these conditions. Wang et al. (2020a) introduced an effective time-domain model for calculating the pressure of blast waves scattered by cylinders and developed a method for examining the transient response of cylindrical substructures under underwater explosion conditions. Their work focused on the scattered pressure waves acting on vertical cylinders and the resulting transient responses. Wang et al. (2014) employed fluid–structure coupling methods for numerical simulations of underwater explosions, comparing the impact characteristics of critical explosive loads. Their research effectively

Article Highlights

- The RKDG finite element coupling model accurately simulated the deformation response of ship hull girders under near-field underwater explosion loads.
- XGBoost and RF machine learning models successfully predicted the maximum deformation of ship hull structures, with XGBoost performing better.
- The XGBoost model demonstrated lower root mean square error and relative error, confirming its prediction accuracy in underwater explosion scenarios.

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described and captured cavitation phenomena near the free surface and structures, offering valuable methodologies for investigating blast waves. Jin et al. (2017) introduced a numerical computation method that couples blast wave loads, calculated using the Runge–Kutta discontinuous Galerkin method (RKDG) with finite element method (FEM) structures. This approach was used to examine the response of sandwich structures to underwater explosive loads, with results verified through comparative experimental analysis. Park (2019) applied the RKDG–FEM combination to simulate internal pipe explosions, analyzing the transmission patterns of blast waves within pipes.

The blast wave loading can induce localized structural damage to varying extents. Considering research on such local damages, Suresh and Ramajeyathilagam (2021) conducted underwater explosion experiments using a small equivalent-weight explosive. They tested mild-steel sheets fixed at the edges and observed deformation, stretching, tearing, and rupture originating from the central part of the sheet. Numerical simulations were used to predict and analyze the permanent deformation trends of the sheets under varying water-bearing conditions. Jiang et al. (2021) examined the underwater impact response of aluminum plates with preexisting cracks. They observed the crack expansion properties and changes in the height of the aluminum plate using an underwater shock tube to simulate the underwater explosive load. Their findings revealed an asynchronous relationship between the crack expansion time and the height increase. They also identified a linear correlation between the sine value of the deviation angle and the radial distance of the final plate shape. Peng et al. (2021) introduced a three-dimensional fluid–structure interaction (FSI) solver that couples smooth particle hydrodynamics (SPH) (Sun et al., 2017) and the reproducing kernel particle method (Liu et al., 1995). They applied this method to simulate local ship structures and grillages, confirming the accuracy and robustness of the FSI solver. Nurick and Shave (1996) conducted experiments and analyses on the responses of circular sheets subjected to underwater contact explosion loads, providing threshold values for several damage modes. Similarly, Wierzbicki (1999) investigated the damage modes of futtock plates under contact explosion loads and introduced an empirical model for crevasse size, considering the deformation rate.

Compared to local damage, overall damage involves more nonlinear factors. In the study of overall damage, Zhang et al. (2015) used experimental methods to examine the characteristics of ship hull girder structure damage under the influence of underwater near-field explosions. Their study preliminarily identified conditions that contribute to arching phenomena in ship hull girder structures under explosive loads and introduced a mechanical model to couple overall and local deformations of the ship hull's girder. He et al. (2020) conducted a series of underwater

explosion tests on ship hull girder structures, combined with numerical simulations, to examine the impact of explosion distance on maximum girder deformation and analyze deformation processes and damage modes. Similarly, Zhang et al. (2015) investigated the responses of ship hull structures using experimental methods, examining the relationship between overall and local deformations. Zong et al. (2013) investigated ship destruction processes attributed to near-field and noncontact underwater explosions, discovering that blast waves primarily govern local structure destruction. Gan et al. (2019) and Zhang et al. (2020) used numerical methods to investigate ship hull girder deformation under underwater explosive loads, confirming overall longitudinal girder strength under combined explosion and wave load conditions. Li et al. (2021; 2024) applied a combined theoretical and experimental approach to examine overall sagging damage due to near-field explosions on ship hull girders, preliminarily explaining conditions for girder sagging behavior.

Overall, previous studies have predominantly used numerical simulations to predict the structural responses of ship hull girders. However, these methods often involve high computational costs and low efficiency. This study employs the RKDG method to calculate near-field underwater explosive loads, integrates finite element analysis to determine the structural responses of ship hull girder structures, and compares training data with experimental results to validate the accuracy of the model, aiming to predict the nonlinear shaping responses of ship hull girders under near-field underwater explosion loads. Furthermore, this study uses two data-driven machine learning models, XGBoost and RF, to dynamically predict maximum girder deformation. Evaluation of these models using root mean square error (RMSE), relative error (RE), and determination coefficient (R^2) indicates that the extreme gradient boosting (XGBoost) algorithm outperforms the random forest (RF) model in terms of prediction accuracy.

2 Experiment design of underwater exploded ship hull girder deformation

2.1 Experimental design

The structural layout of the ship hull girder is depicted in Figure 1 to investigate the structural response of the ship hull girder to blast waves generated by underwater explosions. The ship hull girder is constructed from Q235 material and measures $0.5 \text{ m} \times 0.07 \text{ m} \times 0.03 \text{ m}$. This girder comprises five cabins, each containing a rectangular groove. The distances between the rectangular grooves and the outer surface of the ship hull girder are 15 and 10 mm, respectively, with all steel plates having a thickness of 1 mm. The layout of the explosion test is illustrated in Figure 2. The

ship model is placed on the surface of the water, with a draft reaching half the model's depth. A 4 g explosive is placed under the central part of the ship hull girder, with h representing the explosion distance. The parameters for the simulation test, which ensure model accuracy, are listed in Table 1.

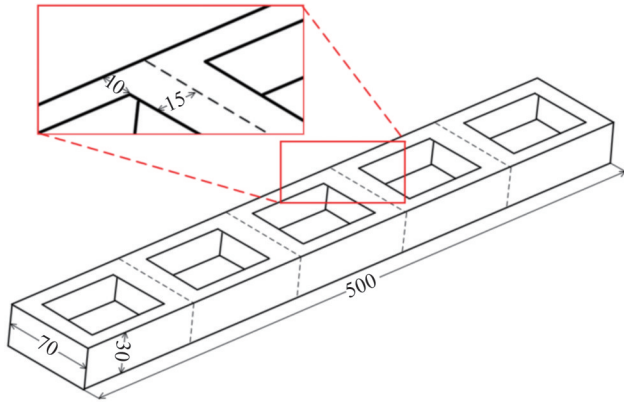


Figure 1 Structural format of the ship hull girder

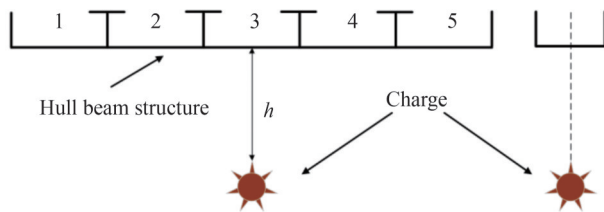


Figure 2 Layout diagram of the explosion test

Table 1 Working condition parameter of the underwater explosion

Working condition serial number	Explosion distance (mm)	Explosive type	Equivalent weight (g)
1	50	TNT	4
2	75	TNT	4
3	100	TNT	4

2.2 Experimental result

The final deformation results of the ship hull girder structure in the experiment, at various time points, are depicted in Figure 3. This deformation is characterized by the vertical distance between the center and both ends of the overall deformed ship hull. Notably, the overall deformation increases as the distance from the center decreases. Additionally, at $T = 0.6$ ms, a plastic hinge forms in the central part of the ship hull girder, accompanied by localized damage to the overall model. By $T = 1$ ms, the entire structure of the ship hull girder moves upward, with the overall deformation remaining constant.

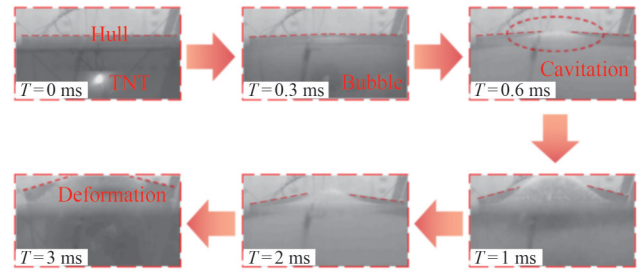


Figure 3 Experimental result (He et al., 2020)

3 Theoretical method

3.1 Runge–Kutta discontinuous galerkin method

The discontinuous Galerkin method, a spatial discretization technique for differential equations, offers high precision similar to the finite element and finite volume methods. This method excels without necessitating large-scale templates, demonstrating excellent compactness. Introducing the concept of numerical flux facilitates the calculation of flow field interactions between units, enabling the capture of strongly discontinuous blast wave transmission and charge initiation modes. Moreover, this method incorporates various nonlinear limiters to suppress nonphysical shocks while maintaining accuracy.

In the context of underwater explosions, the surrounding water postdetonation is assumed to behave as a compressible flow field with inviscid and irrotational properties. Herein, the fluid density is denoted by ρ , speed by (u, v, w) , and pressure by P . The term S on the right side accounts for the influence of gravity, while the total energy per unit volume is denoted by E . Therefore, the set of hydro-mechanical equations (Cockburn et al., 1990; Qiu et al., 2008) exhibiting strong compressible characteristics can be expressed as follows:

$$U_t + \nabla \cdot F(U) = S(U) \quad (1)$$

$$U = \begin{bmatrix} \rho \\ \rho u \\ \rho v \\ \rho w \\ E \end{bmatrix}, f(U) = \begin{bmatrix} \rho u \\ \rho u^2 + p \\ \rho uv \\ \rho uw \\ u(E + p) \end{bmatrix}, h(U) = \begin{bmatrix} \rho w \\ \rho wu \\ \rho wv \\ \rho w^2 + p \\ w(E + p) \end{bmatrix},$$

$$E = \rho e + \frac{1}{2} \rho (u^2 + v^2 + w^2)$$

where $w = 0$ represents the two-dimensional Euler equation, ensuring the relation: $U + F + G = S$.

$$U_t + F_x + G_y = S \quad (2)$$

$$U = \begin{bmatrix} \rho \\ \rho u \\ \rho v \\ E \end{bmatrix}, F = \begin{bmatrix} \rho u \\ \rho u^2 + p \\ \rho uv \\ u(E + p) \end{bmatrix}, G = \begin{bmatrix} \rho v \\ \rho vu \\ \rho v^2 + p \\ v(E + p) \end{bmatrix},$$

$$E = \rho e + \frac{1}{2} \rho (u^2 + v^2)$$

Assuming the symmetry axis as the y axis, incorporating the axisymmetric component into the right-hand side term S yields the following:

$$S = -\frac{1}{x} \begin{bmatrix} \rho u \\ \rho u^2 \\ \rho uv \\ u(E + p) \end{bmatrix} \quad (3)$$

Eq. (3) can be used in the calculation of the two-dimensional axial symmetry model, drastically reducing the number of calculated units and enhancing computational efficiency. However, the applicability of this model is fairly limited.

In the quadrilateral unit $[x_{i-1/2}, x_{i+1/2}] \times [y_{j-1/2}, y_{j+1/2}]$, the approximate solution $\hat{U}(x, y, t)$ is obtained as follows:

$$\hat{U}(x, y, t) = \bar{U}(t) + U_x(t)\xi_i(x) + U_y(t)\eta_j(y) + U_{xy}(t)\xi_i(x)\eta_j(y) + U_{xx}(t)\left(\xi_i(x)^2 - \frac{1}{3}\right) + U_{yy}(t)\left(\eta_j(y)^2 - \frac{1}{3}\right) \quad (4)$$

where $\xi_i(x) = \frac{x - x_i}{\Delta x_i/2}$, $\eta_j(y) = \frac{y - y_j}{\Delta y_j/2}$, $\Delta x_i = x_{i+1/2} - x_{i-1/2}$, $\Delta y_j = y_{j+1/2} - y_{j-1/2}$ are basic functions, and the final form is shown as follows:

$$U_t = R(U) \quad (5)$$

where $R(U)$ is the discrete operator of the spatial derivative.

Discretization of Eq. (5) using the third-order Runge-Kutta method yields the following discrete difference:

$$\begin{cases} U^{(1)} = U^{(n)} + \Delta t R(U^{(n)}) \\ U^{(2)} = \frac{3}{4}U^{(n)} + \frac{1}{4}[U^{(1)} + \Delta t R(U^{(1)})] \\ U^{n+1} = \frac{1}{3}U^{(n)} + \frac{2}{3}[U^{(2)} + \Delta t R(U^{(2)})] \end{cases} \quad (6)$$

3.2 Numerical simulation and experimental verification

The third section includes two experiments conducted

under different working conditions to examine the deformation of the ship hull girder. Determining certain characteristics, such as Mises stress, strain rate, and equivalent plastic strain induced by the impulse load, is difficult due to experimental limitations. Considering the structural response to blast waves from underwater explosions, numerical simulations are performed under three working conditions. These simulations further investigate the dynamic response of the ship hull girder.

3.2.1 Blast wave load numerical simulation of the discontinuous galerkin method

This study employs a combination of the RKDG method and finite element analysis to achieve high-precision calculations. A numerical simulation of two-dimensional underwater explosive loads is performed using the RKDG method. The pressure-time curve of the blast wave is recorded, and a finite element model of the structure is then created in the commercial finite element software, ABAQUS, for coupling. Finally, ABAQUS is applied to calculate the nonlinear response of the structure.

The underwater explosion model is designed based on the experimental model presented in Figure 4. The fluid area measures $1.2 \text{ m} \times 1.2 \text{ m}$. The charge model comprises a spherical charge with a radius of $r = 8.4 \text{ mm}$ and an equivalent weight of 4 g . As indicated in the figure, the coordinates designate the origin (point O) and the central coordinate of the spherical charge $(0, 0.6)$. The model uses a square grid with uniform distribution, with each grid measuring 1.67 mm , totaling $518\,400$ grids. The initiation mode of the spherical charge is center priming. Multiple RKDG solver models are used for the numerical simulation, with a nonreflective boundary set for the outer domain boundary in this model.

3.2.2 Establishment of the finite element model

This study uses the commercial simulation software ABAQUS to perform numerical simulations, utilizing the

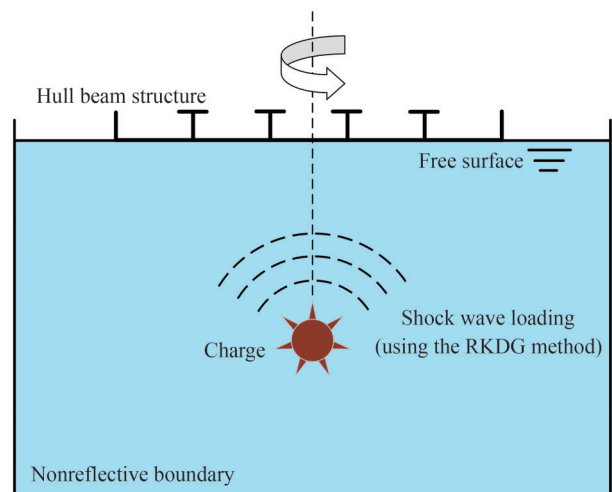


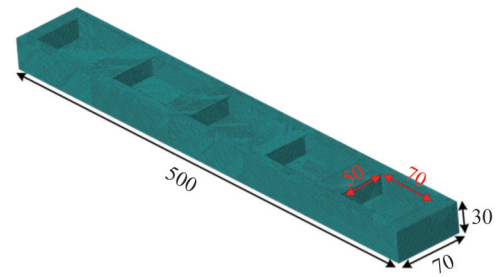
Figure 4 Schematic of the underwater near-field explosion

acoustic–structure coupling method to analyze the effects of underwater explosions. In this process, the acoustic medium replaces the fluid for ABAQUS acoustic–structure coupling simulations. Within this framework, blast wave and bubble pulsation loads are transferred within the acoustic unit. The acoustic medium mainly transmits pressure, ensuring stability in calculations and substantially enhancing simulation efficiency (Zhang et al., 2021a). ABAQUS offers two methods for acoustic simulation: the general wave formula and the scattered wave formula. In this paper, the general wave formula is selected due to its capability to account for fluid cavitation effects and the influence of hydrostatic pressure on the structural response (Wei et al., 2021). The critical pressure for fluid cavitation is set at 0 MPa.

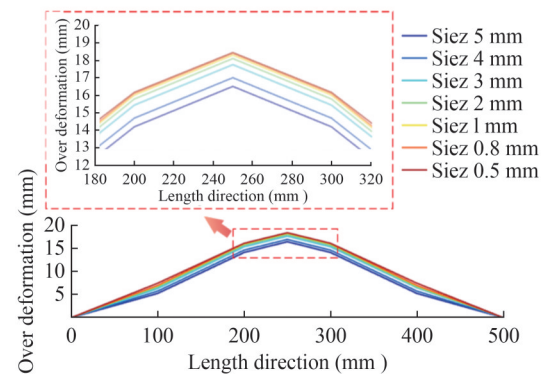
The numerical ship hull girder model, shown in Figure 5(a), features a water area with dimensions of 5 m × 3 m × 3 m. Free boundaries are assigned to the upper surface of the water area, while nonreflective boundaries are applied to the other surfaces. Simulations are conducted under various working conditions, with TNT spherical charges located underwater at depths of 50, 75, and 100 mm, consistent with the experimental setup. For grid division, the model uses AC3D4 acoustic tetrahedron elements to represent the water area. A grid convergence analysis is performed to verify the rationality of the grid sizes. Seven sets of mesh sizes are selected for the simulation, ranging from 5 mm × 5 mm × 5 mm down to 0.5 mm × 0.5 mm × 0.5 mm, to minimize the impact of mesh resolution on the numerical results. The simulation results, presented in Figure 5(b), indicate that as the mesh size decreases and the number of mesh elements increases, the maximum deformation of the hull beam structure gradually increases. However, when the mesh size is reduced from 1 mm × 1 mm × 1 mm to 0.5 mm × 0.5 mm × 0.5 mm, the change in maximum deformation becomes negligible, despite a remarkable increase in computational cost. This finding suggests that reducing the mesh size below 1 mm offers minimal improvements in accuracy while extensively increasing computational expenses. Therefore, the mesh size was finalized at 1 mm × 1 mm × 1 mm. Additionally, the blast wave loads calculated using the discontinuous Galerkin method are imported into the simulation software for further analysis due to limitations in commercial software.

3.2.3 Material parameters

In finite element simulations, plastic constitutive and damage models are commonly used to simulate and illustrate material deformation during impact response. Figure 6 illustrates the relationship between the material's stress and strain, highlighting three stages: the elastic stage (a – b), the plastic stage (b – c), and the damage evolution stage (c – d). This study uses the Johnson–Cook constitutive model for the finite element simulation of Q235 (Cao et al., 2020). The model presents a relational expression for the equivalent stress, equivalent plastic strain, equivalent plastic strain rate, and temperature, as shown in Eq. (7):



(a) Ship hull girder finite element simulation model



(b) Verification of grid independence

Figure 5 Numerical model

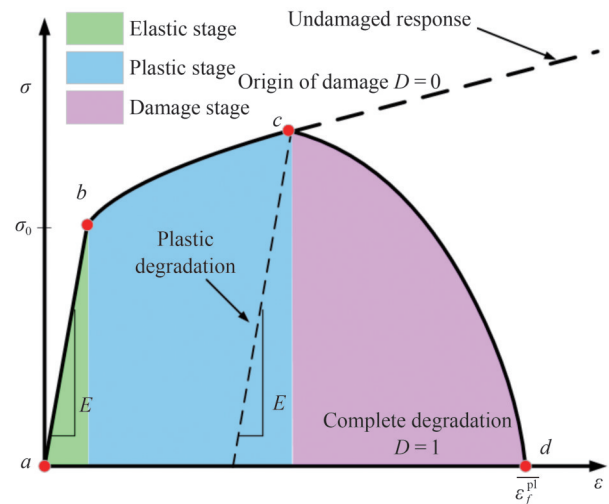


Figure 6 Q235 stress–strain relationship

lent stress, equivalent plastic strain, equivalent plastic strain rate, and temperature, as shown in Eq. (7):

$$\sigma = [A + B\epsilon^n][1 + C \ln \dot{\epsilon}^*][1 - T^{*m}] \quad (7)$$

where σ is the von Mises flow stress, ϵ is the equivalent plastic strain, $\dot{\epsilon}^* = \dot{\epsilon}/\dot{\epsilon}_0$ is the dimensionless normalized plastic strain rate considering the reference strain rate $\dot{\epsilon}$, $\dot{\epsilon}_0$ is the strain rate, and $T^* = (T - T_0)/(T_m - T_0)$ is the homologous temperature of the material. A denotes the yield strength of the material, B denotes the strain hardening coefficient, n represents the strain hardening exponent, C is the strain

rate coefficient, m is the thermal softening parameter, T_0 is the reference temperature, and T_m denotes the melting temperature of the material. The first, second, and third terms in Eq. (1) capture the large strain, strain rate, and thermal softening effects, respectively, during loading. The material parameters for Q235 used in this paper are obtained through Hopkinson pressure bar experiments, and the specific parameters are listed in Table 2.

Table 2 Q235 constitutive parameter (He et al., 2020)

Material	A (MPa)	B (MPa)	C	n	m
Q235	543.75	1363.6	0.127	0.33	0.303

The Johnson–Cook damage model introduced by Johnson and Cook (1985) accurately reflects the failure mechanism of commonly used metal materials. The Formula of this model is presented in Eq. (8) (He et al., 2020):

$$\omega = \sum_{j=1}^n \left(\frac{\Delta \varepsilon^{\text{pl}}}{\varepsilon_D^{\text{pl}}} \right) \quad (8)$$

where $\Delta \varepsilon^{\text{pl}}$ represents the increment of the equivalent plastic strain, and $\varepsilon_D^{\text{pl}}$ represents the failure strain.

Failure behaviors occur when $\omega > 1$ in Eq. (8). The failure strain formula $\varepsilon_D^{\text{pl}}$ is then expressed in Eq. (9):

$$\varepsilon_D^{\text{pl}} = \left[d_1 + d_2 \exp \left(d_3 \frac{\sigma_p}{\sigma_{\min}} \right) \right] \left[1 + d_4 \ln \left(\frac{\dot{\varepsilon}}{\dot{\varepsilon}_0} \right) \right] \left[1 + d_5 \left(\frac{T - T_{\text{room}}}{T_{\text{melt}} - T_{\text{room}}} \right) \right] \quad (9)$$

where $\dot{\varepsilon}_0$ denotes the reference strain rate, $\dot{\varepsilon}$ represents the plastic strain rate, and d_1 , d_2 , d_3 , d_4 , and d_5 represent the failure parameters of the material.

The failure parameter values for Q235, as investigated in this study, are presented in Table 3.

Table 3 Q235 Johnson–Cook failure parameters (Tang and Li, 2021)

d_1	d_2	d_3	d_4	d_5
0.005	3.44	−2.12	0.002	1.61

3.2.4 Results of the blast wave

This study primarily examines the characteristics of underwater explosions using spherical charges and the deformation patterns of ship hull girder structures. The calculation model is depicted in Section 4.1, with the discontinuous Galerkin blast wave model illustrated in Figure 7, indicating rapid propagation of the blast wave in water followed by a sharp decay after reaching its peak.

3.2.5 Numerical model verification

Underwater near-field explosions are common damage loads during vessel attacks. When exposed to these explosive loads, ship hull girders often experience plastic deformation, shear failure, plastic cracking, plastic hinge formation, and other typical damage modes. In addition to accounting for the complex fluid–structure coupling, factors such as TNT equivalent weight and explosion distance must also be considered. Existing theoretical methods often provide only simplistic analytical solutions, which can introduce errors. Therefore, this study combines experiments with numerical simulations to conduct comprehensive analyses.

The near-field explosion load data for spherical charges, obtained through discontinuous Galerkin calculations, are

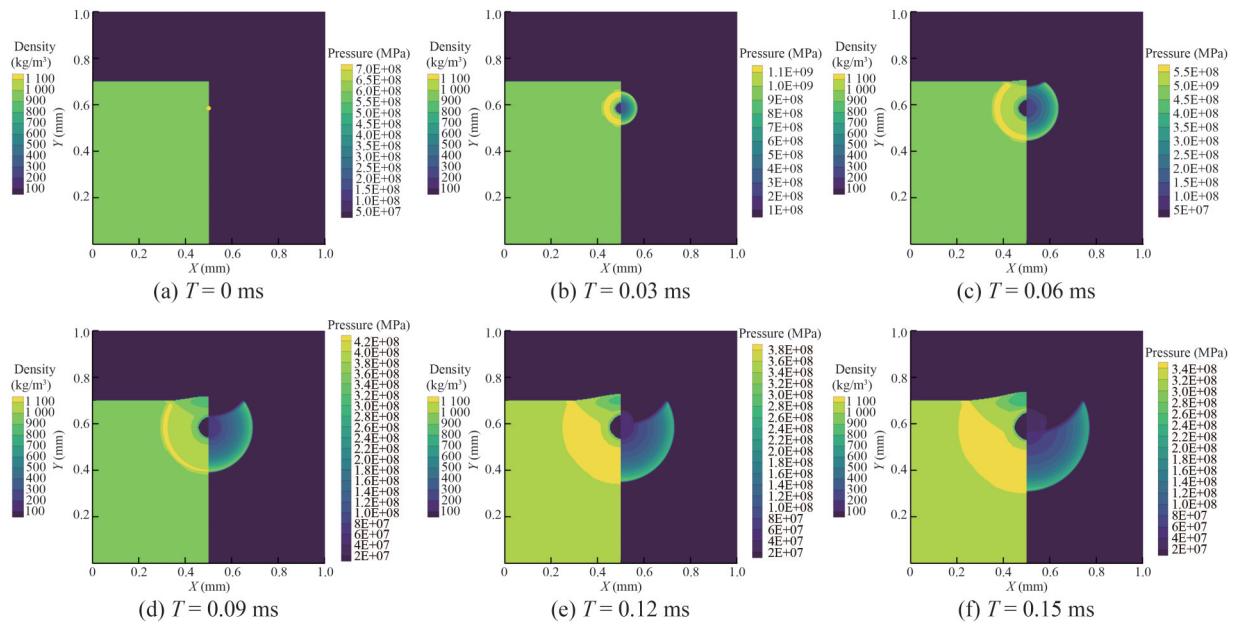


Figure 7 Cloud diagram of the detonation pressure of spherical charge explosion under the water

combined with the ABAQUS solver to simulate the dynamic responses and structural deformations. Using the working condition of the second group as an example, Figure 8 compares the deformation process of the ship hull girder structure with experimental results. This comparison reveals a close alignment between the simulated explosion process and experimental observations. Upon explosion initiation ($t = 0$ ms), the blast wave radiates outward, reaching the bottom of the hull girder at approximately 0.3 ms. This impact leads to rapid deformation, with the central section of the hull arching upward. By $t = 3$ ms, the hull has risen above the water surface, exhibiting rigid-body motion. Notably, the primary deformation of the hull girder structure occurs after 1 ms due to the formation of a plastic hinge at the midsection caused by the shock wave load. This plastic hinge weakens the structural integrity, allowing for greater deformations and strengthening the overall impact on the structural response.

Figure 9(a) displays a curve comparing the maximum deformation of the ship hull girder from numerical simulations and experimental results. The curve indicates a reduction in final deformation with increasing explosion distance and demonstrates relatively good alignment between the numerical and experimental results. The maximum defor-

mation errors for three cases are as follows: Case 1: 19.8%; Case 2: 7.8%; and Case 3: 14.6%. Taking Case 2 as an example, Figure 9(b) compares the hull beam deformation process between the numerical model and the experimental results. When the hull beam is subjected to shock wave loading, deformation occurs in the middle section of the hull beam. In the first 0.6 ms, the maximum deformation is relatively small, accounting for only 29% of the final deformation, revealing a slow structural deformation rate. Between 0.6 and 1 ms, the deformation rate substantially increases, reaching half of the final deformation. This finding is primarily due to the formation of a plastic hinge in the middle section of the hull beam, resulting from earlier structural deformation, weakening the structural strength. The hull beam reaches its maximum deformation at 2 ms. As shown in Figure 9(b), the numerical model agrees well with the experimental results throughout the hull beam deformation process.

3.3 Machine learning predictive model

3.3.1 XGBoost

XGBoost is an optimized and distributed gradient-boosting framework renowned for its efficiency and flexibility.

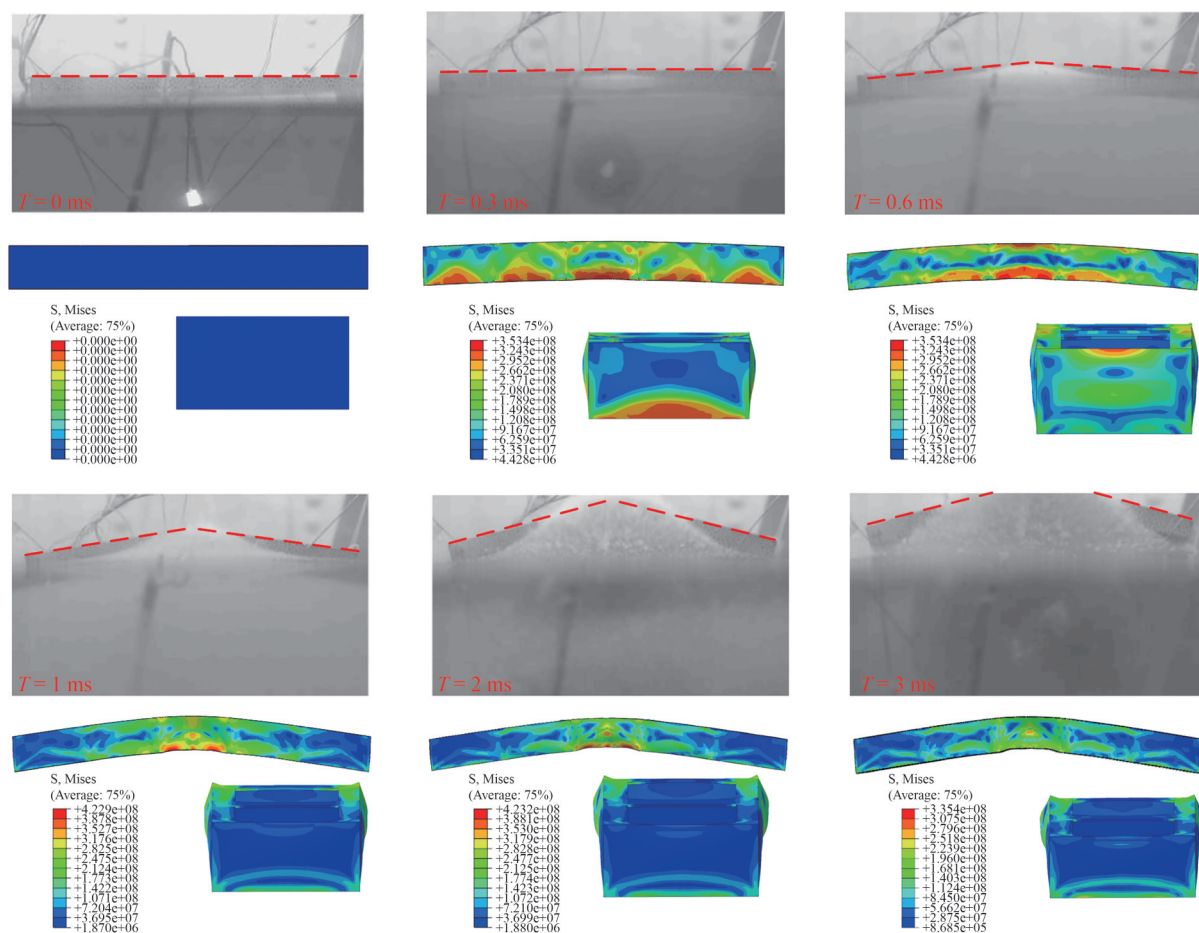


Figure 8 Cloud diagram of the deformation stress of the underwater exploded ship hull girder

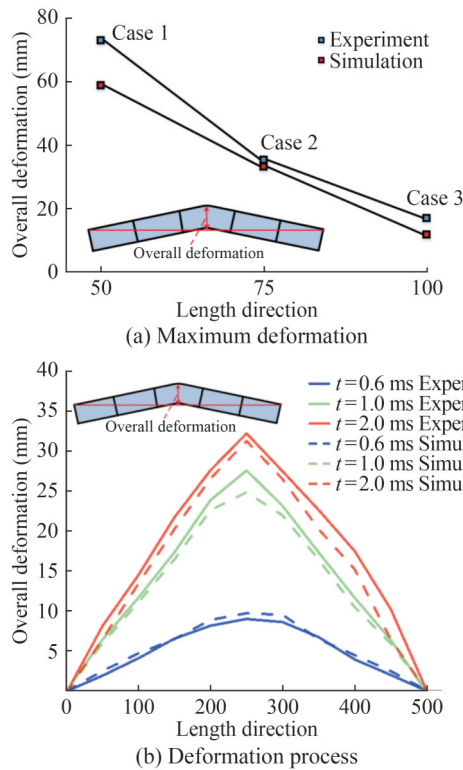


Figure 9 Ship hull girder deformation of the numerical simulation and the experiment

In each iteration, XGBoost adds decision trees to its ensemble. The process begins by training weak learners and gradually enhancing the overall model to create a strong learner. During this process, trees are constructed based on the residuals between predicted and actual data. After each iteration, a new tree is established to further refine the residual calculation, continuously improving model fit (Era et al., 2022). A tree in XGBoost typically has J leaves, represented by Eq. (10) (Zhang et al., 2021b):

$$T(x; \Theta) = \sum_{j=1}^J \gamma_j I(x \in R_j) \quad (10)$$

where $\Theta = \{R_j, \gamma_j\}_1^J$, and γ_j represents the constant related to R_j . The boost tree prediction model aggregates all trees, as shown in Eq. (11), where M denotes the total number of trees:

$$f_M(x) = \sum_{m=1}^M T(x; \Theta_m) \quad (11)$$

The loss function quantifies the disparity between predicted values and actual labels, and optimizing this function helps approximate solutions. The objective function for each optimization step is depicted in Eq. (12):

$$\text{objective}_m = \sum_{i=1}^n L(y_i, f_{m-1}(x_i) + v \cdot T(x_i; \Theta_m)) + \varepsilon \cdot J + \lambda \cdot \sum_{j=1}^J \gamma_{jm}^2 \quad (12)$$

The first part of the objective function $\sum_{i=1}^n L(y_i, f_{m-1}(x_i) + v \cdot T(x_i; \Theta_m))$ represents the loss from predicting y_i using $f_{m-1}(x_i)$ through the m th tree model $T(x_i; \Theta_m)$, combining predictions from previous tree models. The second part of the target function, $\varepsilon \cdot J + \lambda \cdot \sum_{j=1}^J \gamma_{jm}^2$, introduces regularization to mitigate overfitting.

XGBoost employs binary splitting, where the splitting point is selected to maximize the gain, as expressed in Eq. (13).

$$G = \frac{1}{2} \left[\frac{G_L^2}{H_L + \lambda} + \frac{G_R^2}{H_R + \lambda} - \frac{(G_L + G_R)^2}{H_L + H_R + \lambda} \right] \quad (13)$$

The modeling process of XGBoost, illustrated in Figure 10, comprises the following two stages: training and testing. During training, data are input to the model for algorithm training and output production. Subsequently, during testing, the observed results are used to evaluate model accuracy. Parameters are adjusted in accordance with the data types and specific issues to train the model effectively. Residuals are calculated, error weights are assigned to previous models, and new learning occurs. In this study, the training data are extracted from the discontinuous Galerkin method-finite element model, with splitting functions used to separate the training and testing data.

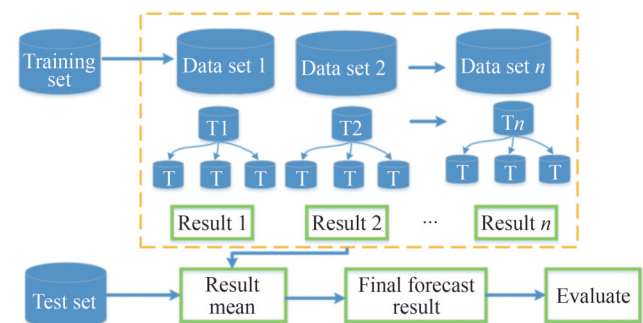


Figure 10 Modeling process of XGBoost machine learning

3.3.2 Random forest (RF)

RF involves training and predicting with multiple decision trees, making it a form of ensemble learning. The fundamental concept of RF lies in combining multiple classifiers to create a stronger classifier with enhanced predictive capabilities. Eq. (14) illustrates the dataset structure:

$$D = \{(X_i, y_i)\} (|D| = n, X_i \in R^m, y_i \in R) \quad (14)$$

where n represents the number of samples in the dataset, and m represents the number of features in each sample. The dataset is divided into training and testing sets, as depicted in Eq. (15):

$$S_L = \{(X_1, y_1), (X_2, y_2), \dots, (X_L, y_L)\} \quad (15)$$

where L denotes the number of training sets. The RF algorithm, as outlined in Figure 11, involves the following steps:

- 1) The Bootstrap method is adopted for random sampling of the training set, allowing for the creation of training and testing aggregates.
- 2) Multiple regression models are established based on the training sets sampled in Step 1.
- 3) The training set is input into the trained regression tree model to obtain predicted values.
- 4) The average of all predicted values serves as the prediction result of the RF model.

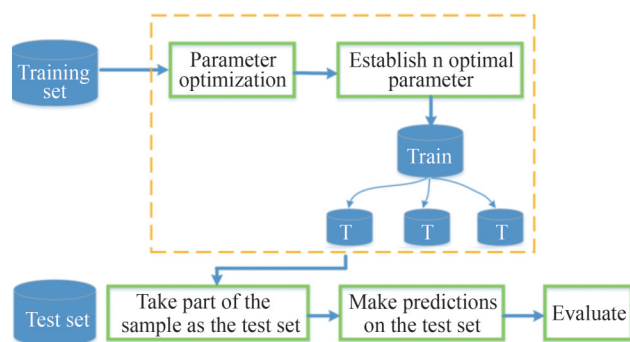


Figure 11 Modeling process of random forest machine learning

In the RF algorithm, the training sets that were not included in the bootstrap process, referred to as out-of-bag samples, lack any data from the training set. Two-thirds of the original training data are typically used to build the regression model, while the remaining data form the out-of-bag sample, which serves as the testing set. The out-of-bag sample is mainly used to evaluate the prediction performance of the RF algorithm, with error calculation detailed in Eq. (16):

$$MSE \approx MSE^{OOB} = \frac{\sum_{i=1}^S [\hat{y}(X_i) - y_i]^2}{S} \quad (16)$$

3.3.3 Data set

Machine learning techniques in this study use the scikit-learn software package (Pedregosa et al., 2011). The module calls are made using the 2019 version of PyCharm, with XGBoost and RF installed in the scikit-learn database. Key functions include XGRegressor and Random Forest Returnor. The decision tree algorithm segments the

dataset into training and testing sets, enabling preprocessing, model training, and evaluation. Consequently, a predictive model is developed to forecast the maximum deformation of the ship hull girder under various explosion distances and equivalent weights.

As a pivotal component of machine learning, the dataset is influenced by the experimental costs. All results from numerical simulations are categorized into training and testing sets. The training set is used to train the XGBoost and RF models, while the testing set is used to evaluate and compare the predictive performance of these models. The accuracy of these models heavily relies on the representativeness of the training set. Therefore, ensuring the representativeness of the training set is crucial for the successful application of XGBoost and RF models across different working conditions. Table 4 presents the parameter table for the training set data, and Figure 12 illustrates the distribution of the training and testing sets, comprising a total of 45 samples. A total of 36 samples generally comprise the training set, while 9 samples form the testing set, as outlined in Table 5.

Table 4 Combination of explosion equivalent weight and explosion distance

Equivalent weight (g)	Explosion distance (mm)
3	10, 15, 20, 25, 30, 35, 40, 45, 50, 60, 70, 75, 80, 90, 100
4	10, 15, 20, 25, 30, 35, 40, 45, 50, 60, 70, 75, 80, 90, 100
5	10, 15, 20, 25, 30, 35, 40, 45, 50, 60, 70, 75, 80, 90, 100

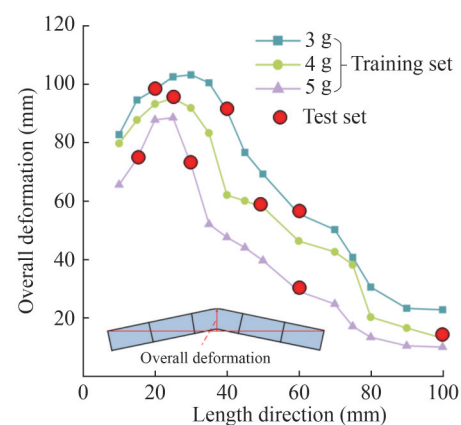


Figure 12 Division of the training and testing sets

4 Result and discussion

4.1 Prediction results

The machine learning model takes the equivalent weight

Table 5 Parameters in the testing set

S/N	Equivalent weight (g)	Explosion distance (mm)	Maximum deformation (mm)
1	3	20	98.165 80
2	3	40	90.959 24
3	3	60	55.561 37
4	4	25	95.118 09
5	4	50	55.847 09
6	4	100	12.956 94
7	5	15	74.387 32
8	5	30	72.450 76
9	5	60	29.020 91

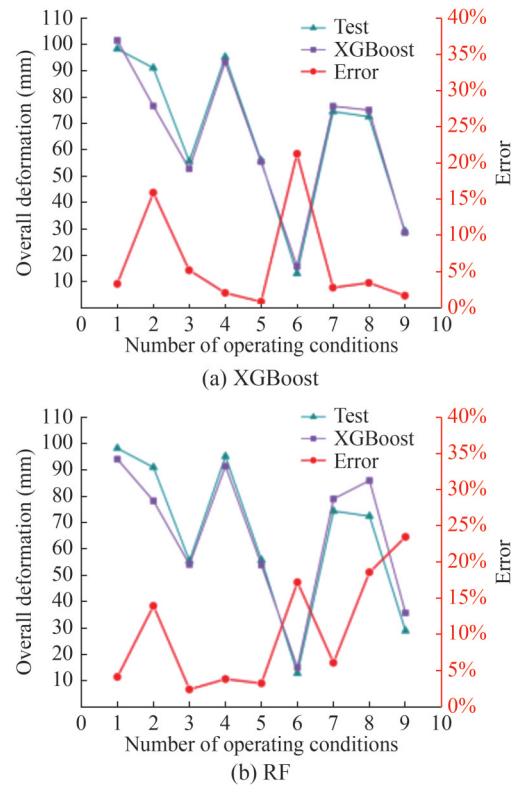
and explosion distance from the dataset as input parameters to predict the maximum deformation of the bulge in the central part of the ship hull girder structure. During modeling, built-in functions, data loading, and definitions are utilized to manage input and output arrays. This study employs Scikit-learn as the database and the 2019 version of PyCharm as the programming module. The XGBoost and RF algorithms are equipped with built-in functions in the Scikit-learn database. Nine sets of data from the numerical simulation results are used as the testing set, while the remaining data constitute the training set. The XGBRegressor() function is used to train the XGBoost model, while the RandomForestRegressor() function is used to define the random forest regressor, set the relevant parameters, call the prediction function, and define evaluation metrics.

The prediction results are used to estimate the maximum deformation of the bulge in the central area of the ship hull girder. Figure 13 depicts the prediction results and error curves derived from the testing sets of the XGBoost and RF models. Both models accurately predict the deformation trend, as indicated by the error curves. However, the errors in the 6th and 9th groups of working conditions in the RF model are relatively large, primarily due to the small true value of prediction. This study assesses the predictive performance and test data to provide insights into accuracy more comprehensively.

4.2 Performance evaluation of XGBoost and RF

4.2.1 Performance evaluation indicator

Performance evaluation is crucial for assessing the accuracy and precision of a model's predictions. In this study, the performance of the XGBoost and RF models in predicting the deformation of ship hull girders subjected to underwater explosions is evaluated using three metrics: root mean square error (RMSE), relative error (RE), and determination coefficient (R^2). Assuming unbiased errors in the prediction and test data, as shown in Eq. (17), calculates the square root of the average of the squared differences

**Figure 13** Results and errors of machine learning

between the predicted and true values. Smaller RMSE values indicate superior model performance.

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{n}} \quad (17)$$

where $\hat{y}_i$ denotes the predicted value, y_i represents the true value, and n is the number of samples.

The relative error (RE) model, as shown in Eq. (18), represents the ratio of the absolute error to the actual measured value, providing insights into the reliability of predictions:

$$\text{RE} = \frac{1}{n} \left| \sum_{i=1}^n \frac{\hat{y}_i - y_i}{y_i} \right| \times 100\% \quad (18)$$

where $\hat{y}_i$ represents the predicted value, and y_i represents the true value.

The determination coefficient (R^2) in Eq. (19) measures the goodness of fit of the model, with values closer to 1 indicating highly accurate predictions.

$$R^2 = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (\bar{y}_i - y_i)^2} \quad (19)$$

where $\hat{y}_i$ represents the predicted value, and y_i represents the true value.

4.2.2 Performance Evaluation

The performance indicators for the XGBoost and RF models are calculated using the scikit-learn metrics. The mean squared error function from the library is used to calculate the RMSE, while the coefficient of determination is directly obtained using the `r2_score` function. The relative error calculation is manually calculated and incorporated into the performance indicators.

Table 6 summarizes the RMSE, relative error (RE), and determination coefficient (R^2) for the predicted values and test data. The determination coefficient reflects how well the model fits the training data. The XGBoost model exhibits a lower RMSE (27.67) compared to the RF model (50.31). Additionally, the XGBoost model fits 96% of the training data, while the RF model fits 92%. The relative error of the XGBoost model (6.25%) is also better than that of the RF model (10.38%). Overall, XGBoost demonstrates better performance and is more suitable for predicting girder structure deformation in underwater exploded ship hulls.

Table 6 Evaluation indicators of the XGBoost model and RF model

Evaluation indicator	RMSE	RE (%)	R^2 (%)
XGBoost	27.67	6.25	96
RF	50.31	10.38	94

Overall, XGBoost proves to be the superior choice for predicting the structural deformation of underwater exploded ship hull girders. This superiority can be attributed to the approach of XGBoost of pruning trees using the “score of similarity” before making predictions (Era, 2022). In this method, the gain function value measures the disparity between the similarity scores of nodes and their child nodes. XGBoost halts tree depth construction once the minimum gain of a node is reached, thereby effectively mitigating overfitting. Conversely, RFs often encounter overfitting due to the similarity of samples across most trees. XGBoost outperforms RFs in handling unbalanced data by focusing on functional space and minimizing function loss, while RFs prioritize hyperparameter optimization.

5 Conclusions

The study of structural response to underwater explosive loads is crucial in fields such as military science and national defense. This paper aims to achieve rapid prediction of ship hull girder deformation under underwater explosive loads. The RKDG–finite element coupling calculation method is used to realize this rapid prediction. By comparing experimental results and precisely simulating the response characteristics of ship hull girders subjected

to near-field spherical charge explosions, we determine the maximum deformation of the ship hull girder. Subsequently, machine learning models, specifically XGBoost and RF models, utilize data derived from the Runge-Kutta discontinuous Galerkin-finite element coupling calculation to dynamically predict the maximum deformation of the ship hull girder structure. Evaluating this method using RMSE, RE, and R^2 reveals that the XGBoost algorithm outperforms the RF algorithm in terms of prediction accuracy.

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