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A hybrid deep learning method for the real-time prediction of collision damage consequences in operational conditions

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ABSTRACT

Ship collisions can result in catastrophic outcomes, necessitating effective real-time collision risk assessment methods for proactive risk management. These methods need to rapidly evaluate both the probability of collision and the potential damage dimensions (length, height, and penetration) in real conditions. Existing frameworks often underestimate collision damage consequences during operational risk assessments. This paper presents a hybrid deep learning approach for the real-time prediction of collision damage dimensions under real ship operation conditions. Collision scenarios are identified using Automatic Identification System (AIS) data, with damage extents simulated through the Super Element (SE) method. A comprehensive database of collision scenarios and corresponding damage assessments is developed, sourced from realistic operational data of Ro-Pax ship in the Gulf of Finland. The deep learning model is trained and validated using this dataset, ensuring the model's relevance and practical applicability. Extensive comparative analyses and generalization tests demonstrate the high accuracy of the model in predicting ship collision damages in diverse ship operational conditions. In addition, traditional simulation methods for evaluating damage dimensions require approximately 10 min, whereas the trained deep learning model reduces the time to less than 0.1 s, enabling real-time potential collision consequence assessment in real operational conditions. The proposed model may provide significant insights for ship operators, enhancing ship safety and supporting intelligent decision-making in ship operations.

1. Introduction

Ship-ship collisions rank among the most frequent and consequential maritime accidents, with potentially catastrophic outcomes including capsizing, sinking, severe environmental damage such as oil spills, and tragic loss of life (Mauro and Vassalos, 2024; Zhang et al., 2021a,b). The stakes are particularly high in passenger shipping, where safeguarding human lives and maintaining ship damage stability in the event of significant flooding are paramount concerns (Ringsberg, 2010; Mauro and Vassalos, 2022; Mauro and Vassalos, 2023; Mauro et al., 2024). In such a context, the development of real-time intelligent decision support systems for collision prevention may be considered essential, especially in complex traffic and environmental conditions (Zhang et al., 2023b; Liu et al., 2024; Gil et al., 2020).

The system risk assessment framework proposed by Kaplan (1997) remains a foundational approach for evaluating collision risk in the time domain. In this model, the assessment function $F(t) = P_C(t)^*C_C(t)$ serves as a critical principle for quantifying collision risk (Arici et al., 2020; Goerlandt et al., 2012; Montewka et al., 2011; Montewka et al., 2014). Specifically, when conducting ship collision risk assessments, it is essential not only to evaluate the probability of collision but also to assess the associated consequences. This dual evaluation—considering both the likelihood of a collision and its potential impact—provides a more comprehensive understanding of collision risk, which is crucial for implementing effective risk mitigation strategies in maritime operations.

Real-time intelligent decision support systems are expected to systematically evaluate both the probability of occurrence $P_C(t)$ and the potential severity of consequences $C_C(t)$ under actual operating condi-

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Nomenclature

P_C (t)	Probability of collision at time t
C_C (t)	Consequence of collision at time t
F (t)	Collision risk function over time, defined as $F(t) = P_C(t)^*C_C(t)$
AIS	Automatic Identification System
SE Method	Super-Element Method
LSTM	Long Short-Term Memory
Transformer	A deep learning model architecture that uses attention mechanisms for capturing long-range dependencies
DBO Algorithm	Dung Beetle Optimization
D_L	Damage Length
D_P	Penetration Depth
D_H	Damage Height
M_0	Fully plastic bending moment in structural analysis
σ_{ij}	Stress tensor component in the structural element
ε_{ij}	Strain rate tensor component in the structural element
Ro-Pax ship	Roll-on/Roll-off Passenger ship
SHARP Model	A software tool used for simulating ship collision and damage scenarios
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
R^2 (R-squared)	Coefficient of determination
δ	Surge velocity of the striking ship
V	Volume of the structural component
E_b	Bending energy rate
E_m	Membrane energy rate
θ_k	Rotation of the k-th hinge in structural analysis
l_k	Length of the k-th hinge
t_p	Thickness of the plate in the structural component
A	Area of the plate in the structural component
σ_0	Flow stress in the structural material
DFT	Damage Frequency Table
FEM	Finite Element Method
ANN	Artificial Neural Network
SVM	Support Vector Machine
K-NN	K-Nearest Neighbors
KG	Vertical distance from the keel to the center of gravity
R_{xx}, R_{yy}, R_{zz}	Radii of gyration in roll, pitch, and yaw directions, respectively
DT	Decision Tree
Bi-LSTM	Bidirectional Long Short-Term Memory
ReLU	Rectified Linear Unit

tions (Gil et al., 2020). Existing methodologies predominantly focus on probabilistic evaluations of collision risk in real conditions, often underestimating the potential collision damage consequences when collisions cannot be avoided (Zhang et al., 2021a,b). This shortcoming highlights the need for advanced models capable of predicting collision consequences in real-time under real conditions, thus ensuring safer ship operations (Zhang et al., 2024a,b; Zhang et al., 2025).

1.1. Literature review

Accurate assessment of ship collision damage consequences is critical for the estimation of the consequences of collisions, including asset loss and potential loss of life due to ship flooding, ship capsizing, sinking, etc. (Mauro et al., 2024; Vassalos et al., 2022; Vassalos and Mujeeb-Ahmed, 2021). Models that evaluate damage dimensions are essential to calculate crashworthiness and potential damage extents. They are crucial for minimizing adverse unavoidable consequences throughout the decision-making processes (Sormunen et al., 2013; Van de Wiel and van Dorp, 2011). These evaluations are a key component of collision risk assessment and support the development of intelligent decision support systems (Zhang et al., 2024a,b; Zhang et al., 2025).

Various methods, including Finite Element Analysis (FEA), empirical studies, and analytical approaches, have been employed to conceptualize ship collision damage (Qu et al., 2024; Kim et al., 2021; Zhang et al., 2019; Liu and Soares, 2023). They primarily address the internal and external mechanics of ship collisions. External mechanics encompass ship motions influenced by factors such as added inertia, damping effects, evasive manoeuvres, and environmental forces like waves, wind, and currents. During collisions, energy dissipation occurs because of structural deformations caused by contact between ships or between a ship and her environment (Deeb et al., 2017; Zhu et al., 2002; Hogström and Ringsberg, 2013; Youssef et al., 2016). Internal mechanics focus on the structural response of ship components, such as plates, stiffeners, bulkheads, girders, and floors, when subject to collision forces (Chen et al., 2019). To understand these responses, it is crucial to develop crashworthiness models that predict the extent of damage (Bužančić Primorac et al., 2020; Wang et al., 2020; Tabri et al., 2009; Tabri et al., 2018).

Current approaches for collision risk assessment can be broadly categorized into probabilistic and simulation-based methods. Probabilistic approaches estimate the likelihood of accidents based on traffic distributions, historical data, and associated hazards (Zhang et al., 2019). However, these methods are often limited by their reliance on historical data, which can hinder accurate predictions of future scenarios (Kuznecovs et al., 2021). Consequently, numerical models that simulate the physical dynamics of accidents are becoming essential for identifying effective risk control measures (Gholipour et al., 2020). Simulation-based methods are aimed at predicting the structural response of colliding ships. Among them, analytical methods, particularly those based on the upper-bound theorem, are used in deterministic evaluations to calculate energy dissipation in structural components during collision events (Haris and Amdahl, 2013; Heinvee and Tabri, 2015). While FEA is recognized as the most reliable and widely used method for evaluating structural responses in ships due to its ability to provide accurate deformation predictions (Calle et al., 2017, 2020), its computational intensity poses significant challenges, particularly in scenarios requiring real-time analysis. Explicit numerical simulations like FEA often demand substantial computational resources and time, which may not be feasible for real-time applications. To address these limitations, reduced-order models or simplified methods, such as the Super Element (SE) method, are employed (Liu et al., 2018; Pedersen, 2010; Kim et al., 2021). The SE method enables rapid calculations of ship collision damage, making it more suitable for scenarios where computational efficiency is critical. However, it should be noted that the SE method may face challenges in handling the complexities of diverse collision scenarios. Additionally, Automatic Identification System (AIS)-based ship collision detection methods can effectively address the challenge of detecting diverse collision scenarios, further enhancing the applicability of SE methods in dynamic and varied operational contexts (Zhang et al., 2021a,b).

Machine Learning (ML) methods (Artificial Neural Networks (ANN), K-Nearest Neighbors (K-NN), and Support Vector Machines (SVM)), excel in modelling complex nonlinear structural systems under real operational conditions (Thai, 2022; Das et al., 2022). For example, Braidotti et al. (2021) developed a ML model using SVM to predict damage consequences, demonstrating the model's ability to capture flooding mechanisms resulting from ship damage. Similarly, Silionis and Anyfantis (2022) designed an ANN model trained on FEM data to predict ship damage under extreme conditions, offering a faster alternative to traditional methods. Advanced ML approaches have further enhanced real-time damage assessment and flooding risk evaluation, such as the development of a damage evaluation model that captures the nonlinear relationship between collision accident scenarios and damage extents (Mauro and Vassalos, 2023; 2024). Despite these advancements, existing approaches still struggle to reliably quantify the consequences of the potential collisions during real shipping operations, particularly in complex traffic situations.

1.2. Research gaps and contributions

The critical literature review in Section 1.1 indicates that, despite significant advancements in ship collision risk assessment and damage prediction methodologies, several research gaps still remain. Current probabilistic and simulation-based approaches are often limited in their ability to address real-time and real-world complexities, particularly in scenarios involving diverse ship types, dynamic collision scenarios, and environmental conditions. Probabilistic models rely heavily on historical data, which may not capture future scenarios accurately, while simulation-based methods, such as finite element analysis, are computationally intensive and lack real-time of rapid applicability. Although machine learning techniques have demonstrated potential in capturing nonlinear relationships and expediting damage assessments, existing models frequently fall short in reliably predicting collision damage consequences during real operations. This gap underscores the need for advanced, hybrid methodologies that integrate the strengths of traditional physics-based simulation models with the adaptability and efficiency of deep learning to enable accurate, real-time assessments of collision damage consequences under complex real operational conditions.

This paper presents a deep learning-based framework that addresses a critical gap in real-time collision damage consequences evaluation for ship collision risk assessment. The proposed hybrid deep learning model combines the hyperparameter optimization algorithm with advanced deep learning architectures, integrating Long Short-Term Memory (LSTM) networks and Transformer models for effective regression of complex temporal data. The Dung Beetle Optimization (DBO) algorithm is further utilized to update the hyperparameters, enhancing predictive accuracy and overall performance. By integrating AIS data with damage simulations generated through the Super Element (SE) method, the study constructs a comprehensive database derived from real operational data of Ro-Pax ships in the Gulf of Finland. The proposed hybrid deep learning model not only significantly improves the accuracy of damage prediction but also demonstrates robust generalization across a wide range of collision scenarios in real operational environments. Notably, the model's ability to rapidly assess collision consequences—achieving results in less than 0.1 s—offers a substantial computational advantage over traditional methods. This breakthrough enables the evaluation of realistic, potential collision scenarios in real time, providing ship operators with a highly effective tool for enhancing maritime safety and supporting intelligent decision-making in complex traffic conditions. The framework represents a significant advancement in proactive risk management, contributing to more efficient collision prevention strategies.

The rest of this paper is organized as follows. Section 2 presents the research framework and methods, including the comprehensive database, the hybrid deep learning model, and the AI-based surrogate model for collision damage prediction. Section 3 focuses on case studies and results, discussing collision scenarios, ship damage predictions, and evaluations. Section 4 concludes the paper with key findings and future research directions.

2. Research framework and methods

In this paper, the SE method is employed to develop a comprehensive database that encompasses collision scenarios and associated damages. A hybrid deep learning model, combining Long Short-Term Memory (LSTM) networks and Transformer models, is utilized. The Dung Beetle Optimization (DBO) algorithm is applied to optimize the hyperparameters of this Transformer-LSTM model. The trained ship damage prediction model is then tested and validated, with a particular focus on Ro-Pax ships operating in the Gulf of Finland. The methodology presented comprises the following three steps (see Fig. 1).

- Step I: Development of a comprehensive database of collision scenarios and associated damages

In this step, a detailed database is created by simulating various collision scenarios using AIS data and incorporating key ship-related parameters such as ship type, speed, and collision angle, etc. The SE method is employed to idealize the damage extends. For each simulated collision scenario, collision breaches are assessed using the SE method in software SHARP (Conti et al., 2021). This method allows for a more precise representation of the structural impact during collisions. Then, a comprehensive database is created, encompassing over 5500 collision scenarios and their associated damages. This database serves as the foundation for training the predictive model. It therefore ensures that it is grounded in realistic and diverse scenarios.

- Step II: Hybrid deep learning model development for collision damage prediction

In this step, a hybrid deep learning model is developed by integrating LSTM networks with attention mechanisms and Transformer architecture. The LSTM network is particularly effective in capturing long-term dependencies in sequential data, while the Transformer model enhances the network's ability to focus on the most relevant features within the data streams. The Dung Beetle Optimization (DBO) algorithm is employed to update the hyperparameters of the Transformer-LSTM model. The choice of DBO is because of its proven efficiency in handling complex optimization problems with multiple parameters, thus ensuring that the model is not only accurate but also computationally efficient. The final AI-based surrogate model, optimized through DBO, is saved for real-time application. By inputting the dynamic collision information (ship type, ship speed, ship draft, collision angle, etc.) of the collision scenario, the model can calculate potential collision consequences within 0.1 s (see more in Section 3). This model is specifically tailored for predicting ship collision damages in the Gulf of Finland, potentially allowing it to be directly applicable to real collision scenarios.

- Step III: AI-based surrogate model for real-time collision damage prediction

The AI-based surrogate model undergoes extensive validation using k-fold cross-validation techniques to ensure its robustness and accuracy. Performance metrics namely the R-squared, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) are used to benchmark the model against traditional methods. The validated model is then applied to real collision scenarios, with a particular focus on Ro-Pax ships in the Gulf of Finland. This application tests the model's generalization capabilities. It ensures that it can accurately predict collision damage in diverse operational conditions. The results are analysed to validate the model's predictions, comparing them against actual simulated data. The potential for future applications is also explored, particularly in terms of enhancing maritime safety protocols and the operational decision-making processes.

2.1. Comprehensive database of collision scenarios and associated damages

The database presented in this section encompasses over 5500 ship collision scenarios and their associated damages. It forms the foundation

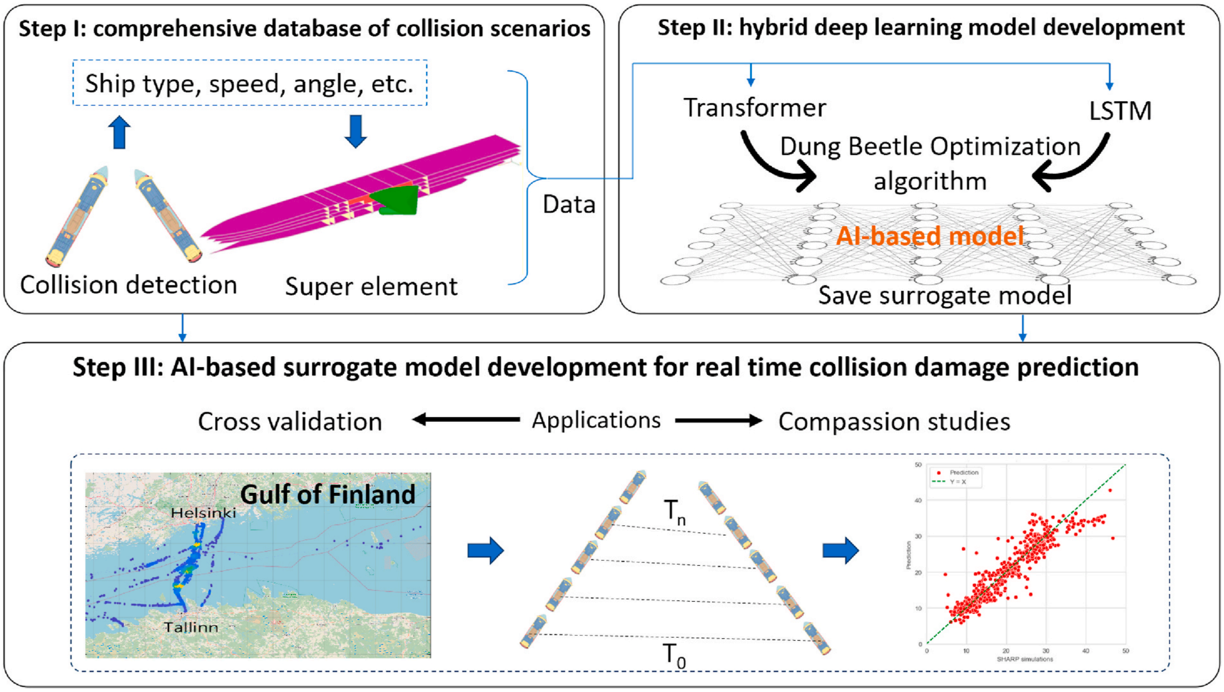


Fig. 1. The deep learning-based framework for the prediction of ship damage in real conditions.

for training predictive models, thus ensuring they are grounded in realistic and diverse scenarios. By meticulously cataloguing details from numerous simulations conducted with SHARP software (Conti et al., 2021), the database captures critical parameters like ship specifications, collision angles, impact velocities, and associated damage dimensions. The data enhance the accuracy and reliability of predictive models.

2.1.1. Super element method

The SE method is employed to model the ship structure using large-sized structural units, referred to as super elements. This approach leverages closed-form analytical formulations that have been extensively validated in Simonsen and Ocakli (1999) and applied in the literature (Conti et al., 2021; Le Sourne et al., 2021). These formulations, derived from principles of plastic limit analysis and supported by experimental data, characterize the resistance and energy dissipation properties of SE, which vary depending on their structural type and the specific deformation mechanisms they undergo. Additionally, previous studies indicate that the SE solvers, SHARP, have been shown to be both accurate and efficient in solving the collision mechanics of ships (Kim et al., 2022).

During a collision, as the impacting ship penetrates the structure of a struck ship, the super elements are sequentially activated. The contribution of each activated SE to the total collision force is then evaluated. The force F leading to the collapse of a given structural component is determined using the upper-bound theorem (Jones, 1989), shown as:

$$F\cdot\dot{\delta} = \iiint_V \sigma_{ij}\cdot\dot{\epsilon}_{ij}\cdot dV \tag{1}$$

where, $\dot{\delta}$ is the surge velocity of the striking ship, σ_{ij} represents the stress tensor of the component, $\dot{\epsilon}_{ij}$ d enotes the strain rate tensor of the component, and V is the volume of the structural component.

To facilitate for an analytical derivation of the force F, two assumptions are made: (1) The material constituting the structure is assumed to behave as a perfectly rigid-plastic solid, and (2) Shear effects near the edges of the plate are neglected, allowing for the internal energy rate to be computed as the sum of bending and membrane contributions, which are considered fully uncoupled.

If we consider a plate in a plane-stress condition, assuming that bending deformations are localized within m plastic hinges, the bending energy rate $\dot{E}_b$ and membrane energy rate $\dot{E}_m$ can be calculated using

$$\dot{E}_b = M_0\sum_{k=1}^{m}\dot{\theta}_k l_k \tag{2}$$

$$\dot{E}_m = \frac{2\sigma_0 t_p}{\sqrt{3}}\iint_A \sqrt{\dot{\epsilon}_{11}^2+\dot{\epsilon}_{22}^2+\dot{\epsilon}_{12}^2+\dot{\epsilon}_{11}\dot{\epsilon}_{22}}\cdot dA \tag{3}$$

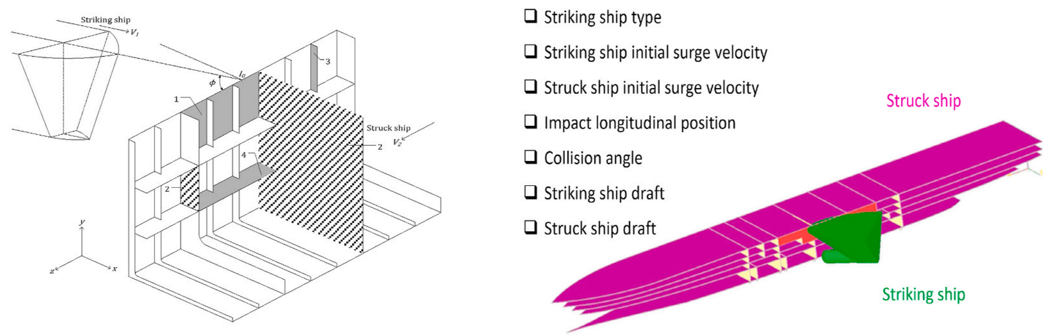
where M_0 represents the fully plastic bending moment, σ_0 is the flow stress, A and t_p denote the area and thickness of the plate, respectively, and θ_k and l_k are correspond to the rotation and length of the k-th hinge.

The SE method is implemented within the SHARP software, thus enabling detailed modelling of ship structures during collision events. As depicted in Fig. 2 (a), the model categorizes the struck ship into four distinct types of SE namely (1) Hull and longitudinal bulkheads, (2) Vertical frames and transverse bulkheads, (3) Secondary stiffeners, and (4) Stringers, decks, and bottom structures. This classification allows for an accurate representation of the structural behaviour under collision forces, thus providing critical insights into the energy dissipation and failure mechanisms during maritime accidents.

In SHARP, a collision scenario is defined in Fig. 2 (b), where the damage bounding box is estimated based on the calculated penetration and the geometry of the striking ship's bow.

2.1.2. Struck ship and geometrical damage model

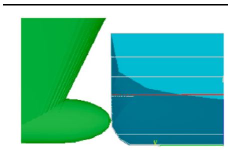
In this paper, the struck ship was modelled using the SE approach over a 100-m section centered in way of the mid-ship area, with SE components defined for the side shell, decks, transverse and longitudinal bulkheads, see Table 1. To optimize computational efficiency, continuous decks with uniform thickness were modelled, while floors, girders, and secondary rooms were excluded. All materials were treated as rigid-perfectly plastic, using S235 mild steel properties, see Table 1. The membrane strain was calculated for the impacted SE and compared to a 10% failure strain, as proposed by Lützen (2001). For decks and bulkheads, the deformation was modelled by a concertina splitting mode followed by edge tearing, with resisting forces compared to empirical



(a) different types of super-elements of ship b) a ship- ship collision scenario

Fig. 2. Super element method to simulate ship collision damage.

Table 1
Struck ship SHARP model and material parameters.



Parameter	Value	Parameter	Value
LPP [m]	216.8	Yield Strength [MPa]	235
Breath moulded B [m]	32.2	Tensile Strength [MPa]	400
Depth D [m]	16	Flow Stress [MPa]	317.5
Draft Dr [m]	7.2	Failure Strain [-]	10%
Displacement [tons]	33 923		

thresholds derived from weld characteristics (Taimuri et al., 2022). The ship hydrodynamic properties, necessary for the MCOL method (external dynamics solver within SHARP software), were obtained via BV Hydrostar software (Kim et al., 2022), with input data detailed in Table 2, assuming infinite water depth and no forward speed.

Before discussing the crash analysis results, it is crucial to establish the framework for damage characterization. From a geometric perspective, collision-induced damage (leakage opening) is represented as a box. This box features two surfaces aligned with the waterplane, two aligned with the transverse plane of the ship, and two shaped to follow the hull's longitudinal contour at the waterline. It intersects both the waterline and one side of the ship. The damage is characterized by six geometrical parameters namely ind_{side}, X_c, L_x, L_y, z_{UL}, z_{LL}, see Fig. 3. Accordingly, the damage height can be defined as: $D_h = z_{UL} - z_{LL}$. In SOLAS (IMO, 2006), the lower vertical damage limit z_{LL} is typically not treated as a random variable, with a worst-case approach being used for computing the *s*-factor in case of horizontal subdivision below the waterline. Bulian et al. (2019) introduced the probabilistic approach to this parameter, which is used in this paper. The method incorporates the probabilistic description of z_{LL} within the extended SOLAS framework.

2.1.3. Collision scenarios and associated damages calculation

Collision scenarios at sea can be detected using AIS data, see Zhang et al. (2021a,b). The identified collisions and their relative striking positions can be classified into the following categories: (a) head-on, (b) front-side, (c) frontal, (d) back-side, and (e) rear-end, as illustrated in Fig. 4. The parameters characterizing each collision scenario can be extracted, as demonstrated in Fig. 2 (b) and Table 3. These parameters enable the descriptions of ship collision scenarios and the estimation of the probable relative collision location along the ship hull and collision energy, which are critical for conducting a thorough ship collision damage analysis.

Additionally, based on our previous study (Zhang et al., 2021a,b), AIS data was used to identify all ships posing collision risks to Ro-Pax ships in the Gulf of Finland. Through this analysis, 11 representative striking ship types were categorized. This selection reflects real-world scenarios in a region with significant maritime activity, ensuring the practical applicability and relevance of the study. The striking ships are categorized into 11 clusters, with their general characteristics detailed in Table 3, while the information pertaining to the struck ship is provided in Table 4. The primary objective of this super element method is to calculate the damage dimensions for a specific ship under operational conditions. In SOLAS (IMO, 2018), the damage distributions assume that a breach occurred following a collision event. Therefore, all potential collision scenarios are simulated on the reference ship, treated as the struck ship (Table 1), using the crash analysis software SHARP. Results of these SHARP simulations are summarized in Table 5. They demonstrate ship collision damage length D_L, penetration D_P, height D_H etc, see Fig. 3.

In addition to the comprehensive simulations, the collision scenarios and the corresponding damages have been meticulously catalogued to construct a database, that comprises of over 5500 collision scenarios and their associated damages and consists of the backbone of the predictive model, see Section 3.1. By incorporating such a wide range of realistic and diverse collision scenarios, the deep learning model can be trained to provide accurate and reliable predictions of various collision scenarios.

Table 2
The input data used for hydrodynamic calculations in Hydrostar.

Parameter	Value
Draft [m]	7.2
Displacement [tons]	33 923
KG [m]	15.14
Gyration radius in roll Rxx [m]	11
Gyration radius in pitch Ryy [m]	60
Gyration radius in yaw Rzz [m]	61

2.2. A hybrid deep learning model for collision damage prediction

The proposed deep learning model synergizes the strengths of traditional machine learning techniques with advanced deep learning architectures to effectively manage complex temporal data. Specifically, the model integrates LSTM networks and Transformer models, leveraging their respective advantages in regression modelling. Additionally, a DBO algorithm is employed to update the hyperparameters of the hybrid model, thereby enhancing its predictive accuracy and overall performance.

2.2.1. Transformer-LSTM model with DBO algorithm optimization

Although LSTM can handle long data sequences, there may be attenuation for very long sequence messaging. However, the self-

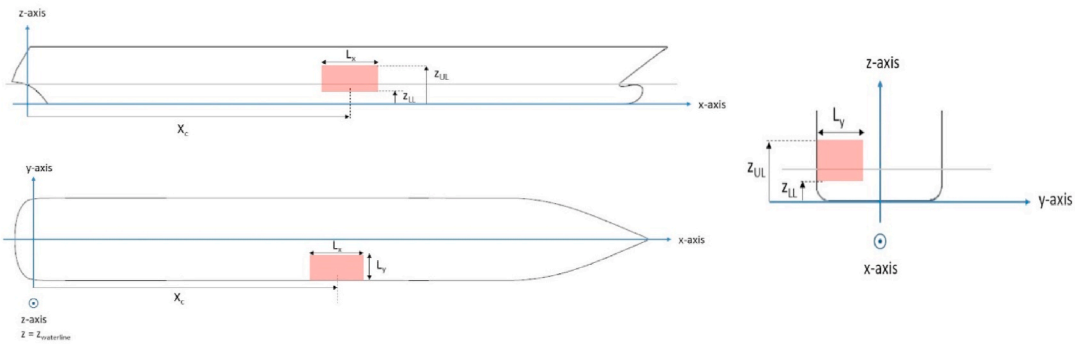


Fig. 3. The overview of ship collision damage geometrical parameters. (ind_{side}: Damage side, Port side (+1) or starboard side (−1); X_c: Longitudinal position of the center of the damage [m]; L_x: Longitudinal extent of the damage/Damage Length [m]; L_y: Transversal extent of the damage/Penetration [m]; z_{UL}: Damage vertical position upper limit [m]; z_{LL}: Damage vertical position lower limit [m]).

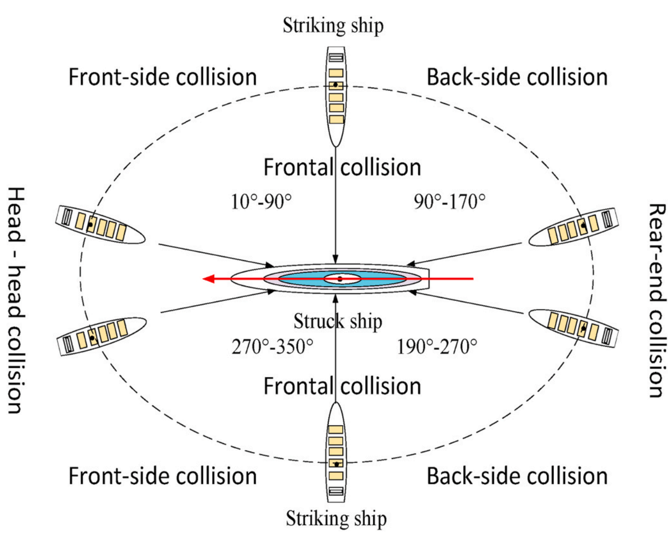


Fig. 4. Collision scenarios relative striking positions (Zhang et al., 2021a,b).

Table 3
Collision scenario parameters.

Collision scenario parameters					
Scenario id	Scenario ID per striking ship	Striking ship id	Length Overall [m]	Breadth Moulded [m]	Max. Draft [m]
Striking Ship initial surge velocity [m/s]	Striking ship draft [-]	Struck Ship initial surge velocity [m/s]	Struck Ship draft [-]	Collision angle [deg]	Collision location [m]

attention mechanism in a Transformer can directly capture the relationship between any two positions in a sequence, regardless of distance.

Combining LSTM and Transformer models leverages the sequence memory capability of LSTM and the global modelling capability of a Transformer. Thus, a hybrid model can capture long-distance dependencies more effectively and can enhance the extraction of diverse features, see Fig. 5. The input data $X = (x_1, x_2, \ldots, x_t)$, containing information for the past t moments, is processed by LSTM to output hidden states $(H_1, H_2, \ldots, H_t)$. These hidden states are then fed into the Transformer's encoder, which processes them through its attention and feed-forward layers. The final output of the Transformer is passed through a fully connected layer to match the target values dimensionality.

This hybrid deep learning model significantly enhances real-time collision damage prediction by combining the strengths of LSTM and Transformer models, enabling the predictive model to accurately capture complex temporal patterns and long-range dependencies that are crucial for predicting associated collision damage of potential collision scenario with greater precision.

2.2.1.1. Long Short-Term Memory (LSTM). Conventional Recurrent Neural Networks (RNNs) suffer from gradient explosion and vanishing issues that may limit their performance in long sequence predictions (Yu et al., 2019). To address this, the LSTM model introduces three gates namely input, output, and forget. These gates allow for effective utilization of the long-distance temporal information and improve the model's learning capability.

As shown in Fig. 6, at a time step t, the current input is combined with the previous hidden state and processed by the Sigmoid (σ) activation function to compute the gate values as Eqs. (4)–(6).

$$F_t = \sigma(W_F \cdot [H_{t-1}, X_t] + b_F), \tag{4}$$

$$I_t = \sigma(W_I \cdot [H_{t-1}, X_t] + b_I), \tag{5}$$

$$O_t = \sigma(W_O \cdot [H_{t-1}, X_t] + b_O), \tag{6}$$

where W_F, W_I, W_O are the weight matrices of the forget, input and output gates, and b_F, b_I, b_O are their respective biases.

The candidate memory element $\widetilde{C}_t$ was computed as shown in Eq. (7), using tanh as the activation function. In this way some information has been retained by multiplying the output of the forget gate, F_t with the hidden state H_{t-1}. By adding the memory cell to the information obtained after the oblivion gate selection we can obtain the new cell state C_t. Finally, the latest hidden state H_t is obtained by combining the output gates O_t and C_t as shown in Eqs. (8) and (9).

$$\widetilde{C}_t = tan\,h(W_c \cdot [H_{t-1}, X_t] + b_c), \tag{7}$$

$$C_t = F_t{*}H_{t-1} + I_t{*}\widetilde{C}_t, \tag{8}$$

$$H_t = O_t{*}tan\,h(C_t). \tag{9}$$

2.2.1.2. Transformer model. The Transformer model utilizes multi-head self-attention mechanisms and an encoder-decoder architecture to extract deep features from big data streams (Han et al., 2022). Unlike other neural networks, Transformers can handle larger datasets, provide higher predictive performance, and have superior learning capabilities (Zhang et al., 2023b, 2024). As shown in Fig. 7, a Transformer's encoder consists of a stack of N identical layers, each with two sub-layers namely a multi-head self-attention mechanism and a fully connected feed-forward network. Both networks are normalized and use residual

Table 4
The ID of the striking ships and their general characteristics.

ID	Type	Length Overall [m]	Breadth Moulded [m]	Min. Draft [m]	Inter. Draft [m]	Max. Draft [m]	Depth [m]	Displacement @maxDraft [tons]	Structure
1	Cargo Vessel 1	92	14,0	3,3	4,3	4,9	10,0	3500	Rigid
2	OSV	80	17,6	4,0	5,7	6,9	13,8	3500	Rigid
3	Chemical Carrier	110	19,5	5,5	6,8	7,6	10,6	11 064	Rigid
4	Gas Carrier	155	22,7	5,5	6,4	6,9	18,0	16 006	Rigid
5	Cargo Vessel 2	145	15,9	4,8	6,7	8,0	11,2	15 415	Rigid
6	RoRo Vessel	180	30,5	5,5	6,3	6,8	15,8	22 062	Rigid
7	Passenger Vessel	251	28,8	5,6	6,2	6,6	19,4	29 558	Rigid
8	RoPax Vessel	221	30,0	5,9	6,5	6,9	15,3	30 114	Rigid
9	Bulk Carrier	180	30,0	5,7	8,3	10,0	15,0	50 000	Rigid
10	Container Vessel	300	48,2	8,0	10,7	12,5	24,6	119 130	Rigid
11	Tanker	274	42,0	8,9	12,5	14,9	21,0	140 000	Rigid

Table 5
The associated ship collision damage parameters from SHARP software.

Damage bounding box output from crash analysis						
Computation status [-]	Damage Length D_L [m]	Penetration D_P [m]	Waterline z_{UL} [m]	Bottom z_{LL} [m]	Damage Height D_H [m]	Dissipated energy [MJ]

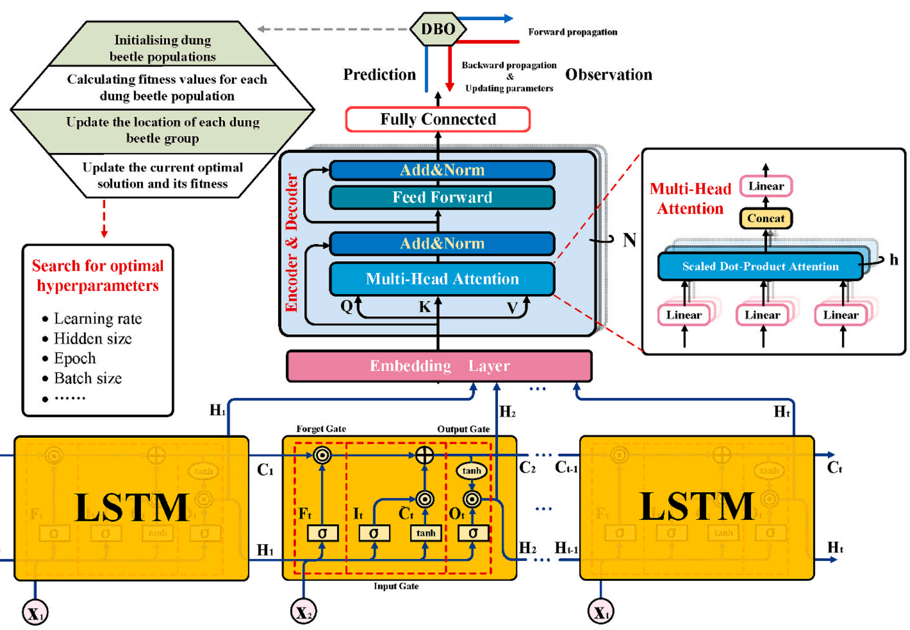


Fig. 5. The structure diagram of Transformer-LSTM with DBO optimization algorithm.

connections. The decoder similarly consists of N identical layers, with an additional sub-layer to masked attention heads.

The input data, combined with positional encoding, is first processed by the encoder consisting of N identical layers. The final output is obtained through a linear layer, which maps the decoder's output to continuous values for regression predictions.

In a Transformer model, position encoding is added to the model as follows:

$$PE_{(pos,2i)} = sin\left(pos \,/\, 10000^{2i/d_{\mathrm{model}}}\right), \tag{10}$$

$$PE_{(pos,2i+1)} = cos\left(pos/10000^{2i/d_{\mathrm{model}}}\right), \tag{11}$$

where pos is the position and i is the dimension of the d_{model}.

The attention mechanism computes the scaled dot-product attention as per Eq. (9):

$$Attention(Q,K,V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right)V, \tag{12}$$

The multi-head attention is formulated according to Eq. (13) and each head is defined as shown in Eq. (14).

$$MultiHead(Q,K,V) = Concat(head_1, \ldots, head_h)W^O, \tag{13}$$

$$\text{where } \mathrm{head}_i = \mathrm{Attention}\left(QW_i^Q, KW_i^K, VW_i^V\right), \tag{14}$$

To prevent access to future tokens during training, a causal mask is applied to the self-attention mechanism in decoder. The attention computation becomes as Eq. (15)

$$Masked-Attention(Q,K,V) = \mathrm{Y} = softmax\left(\frac{QK^T}{\sqrt{d_k}} + Mask\right)V, \tag{15}$$

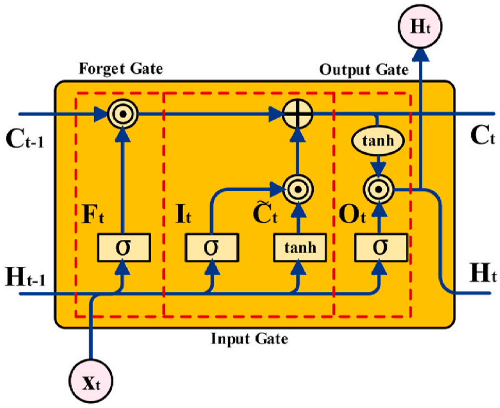


Fig. 6. Long short-term memory neural network structure diagram.

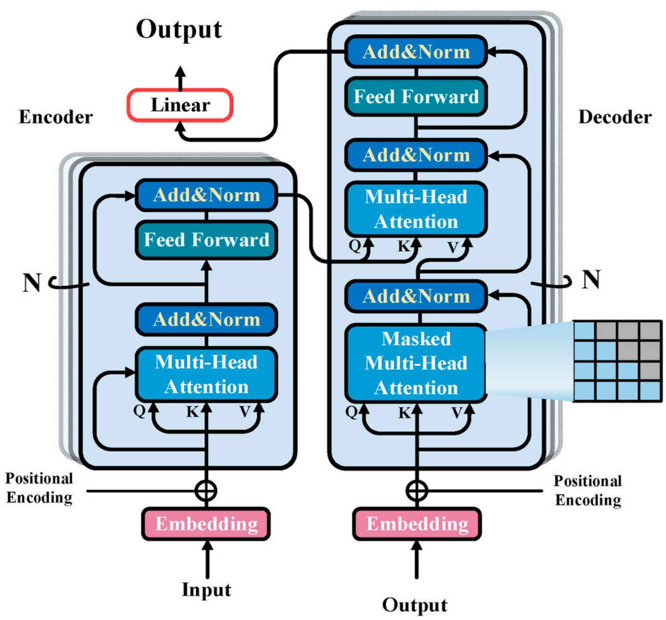


Fig. 7. The diagram of Transformer structure.

where the mask ensures that the model only attends to positions up to the current token.

The feed-forward network applies ReLU activation (Mastromichalakis, 2020) as Eqs. (16) and (17).

$$FFN(x) = max(0, xW_1 + b_1)W_2 + b_2, \tag{16}$$

$$ReLU(x) = (x)^+ = max(0, x) = \begin{cases} x & if x > 0 \\ 0 & if x \leqslant 0 \end{cases}, \tag{17}$$

where Q, K, V are query, key, and value respectively, $\sqrt{d_k}$ is the vector dimension, h is the number of parallel attention heads, W_i^Q, W_i^K, W_i^V are the weight matrices, W_1, W_2 are the weights, and b_1, b_2 are the biases. These components enable the Transformer to capture complex patterns and relationships in data, thus making it a powerful tool for various predictive tasks.

Finally, the encoder-decoder attention attends over the encoder's output. Here, the keys and values come from the encoder's output $Z_{Encoder}$, while the queries are derived from the decoder's previous layer output as Eq. (18).

$$Q = YW_Q, K = Z_{Encoder}W_k, V = Z_{Encoder}W_v, \tag{18}$$

These components, combined with the feed-forward network and causal masking, make the Transformer a versatile model for regression tasks.

2.2.1.3. The DBO algorithm. The Dung Beetle Optimization (DBO) algorithm is population-based optimizer inspired by the active behaviour of dung beetles in nature, i.e., rolling, dancing, foraging, stealing and breeding (Li et al., 2024). As compared with traditional optimization algorithms, the dung beetle algorithm has significant advantages in terms of convergence speed, solution accuracy and stability. Ball-rolling dung beetles roll their dung balls in a straight line to prevent competition from other dung beetles during the rolling process. However, the intensity of the celestial light source or natural factors will cause the dung beetle's travelling path will become curved. During the roll, the Rolling Dung Beetle position is updated as:

$$\begin{aligned} x_i(t+1) &= x_i(t) + \alpha \times k \times x_i(t-1) + b \times \Delta x, \\ \Delta x &= |x_i(t) - X^w|, \end{aligned} \tag{19}$$

where t is the number of iterations, $x_i(t)$ denotes the position of the i-th, dung beetle in the t-th iteration, $k \in (0, 0.2]$ is the deflection coefficient, $b \in (0, 1)$, α is taken as -1 or 1, X^w is the position of the worst dung beetle in the population, and Δx is the simulated change in light intensity.

When the Dung Beetle Roller encounters an obstacle that prevents it from moving forward, it changes its course by dancing to get a new route. The exact location of the update is listed below:

$$x_i(t+1) = x_i(t) + \tan(\theta)|x_i(t) - x_i(t-1)|, \tag{20}$$

where $\theta \in [0, \pi]$ is the deflection angle.

Selection of suitable spawning sites is crucial for dung beetles to provide a safe environment for their offspring. Therefore, a boundary selection strategy is proposed to model the spawning area of dung beetles as:

$$Lb^* = max(X^* \times (1\text{-R}), Lb)\ Ub^* = min(X^* \times (1 + R), Ub) \tag{21}$$

where X^* is the current local optimum, Lb^* is the lower boundary of the spawning region, and Ub^* is the upper boundary of the spawning region, R is the inertia weight.

In the model it is assumed that each female dung beetle lays only one egg in each iteration. The boundary range of the spawning area varies dynamically with the value, so the location of the egg also changes dynamically during the iteration as follows:

$$B_i(t+1) = X^* + b_1 \times (B_i(t) - Lb^*) + b_2 \times (B_i(t) - Ub^*), \tag{22}$$

where $B_i(t)$ is the information about the position of the i-th ovoid at the t-th iteration, b_1 and b_2 are two independent random vectors of size $1 \times$ D, D is the dimension.

Baby dung beetles dig holes in the ground in search of food and their boundaries of the optimal foraging area are defined as:

$$\text{Lb}^\text{b} = \max(\text{X}^\text{b} \times (1\text{-R}), \text{Lb})\ \text{Ub}^\text{b} = \min(\text{X}^\text{b} \times (1 + \text{R}), \text{Ub}) \tag{23}$$

where X^b is the global optimal position, and Lb^b and Ub^b are the lower and upper bounds of the optimal foraging range, respectively. Little Dung Beetle foraging locations have been updated as follows:

$$x_i(t+1) = x_i(t) + C_1 \times \left(x_i(t) - Lb^b\right) + C_2 \times \left(x_i(t) - Ub^b\right), \tag{24}$$

where $x_i(t)$ is the position information of the t-th small dung beetle in t iterations, C_1 is a random number obeying a normal distribution, $C_2 \in (0, 1)$ the random vector.

In populations there will be some dung beetles that steal dung from other dung beetle balls from other dung beetles and are known as Thieving Dung Beetles. The location of the Thieving Dung Beetle can be updated as follows:

$$x_i(t+1) = X^b + S \times g \times \left(|x_i(t) - X^*| + |x_i(t) - X^b|\right), \tag{25}$$

where $x_i(t)$ is the position information of the i-th thief dung beetle at the t-th iteration, g is a random vector of $1 \times D$ and follows a normal distribution, and S is a constant value.

Initially, the DBO algorithm establishes the range of values for the hyperparameters, such as the learning rate, number of neurons, and number of iterations, as well as the initial locations of the dung beetles. Subsequently, the population size for each type of a dung beetle is defined. The algorithm then proceeds to update the positions of the ball-rolling, breeding, small, and thief dung beetles according to the established ranges, applying boundary function constraints on the hyperparameters. Through the fitness function, it evaluates the optimal and worst fitness individuals, comparing the best fitness of the current iteration with the global best fitness. If the current fitness surpasses the global best, the algorithm updates the parameters accordingly. Finally, the algorithm verifies if the termination condition is met. If satisfied, it sets the global optimal parameters for the Transformer-LSTM model. If not, the process is reiterated, continuously refining the model parameters to achieve optimal performance. This iterative optimization ensures that the Transformer-LSTM model attains the highest possible accuracy and efficiency for predicting ship damage dimensions. By integrating these advanced AI techniques and optimization algorithms, this hybrid model significantly enhances the prediction accuracy of ship collision damages in real conditions.

2.2.2. Model evaluation

A predictive model that leverages the hybrid deep learning model introduced in Section 2.2.1 has been developed to capture the complex dynamics of collision scenarios and the resulting damage dimensions in real conditions. This model is designed to represent the nonlinear relationships between dynamic collision risks and their consequences with precision. The predictive accuracy of the model is rigorously evaluated against historical operational data using metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), coefficient of determination (R^2), as defined in Eqs. (24–26). To ensure a robust assessment of the model's generalization capability, the widely recognized k-fold cross-validation method is employed. This involves dividing the dataset into k equally sized subsets, or folds, and iteratively using each fold as a validation set while the remaining k-1 folds serve as the training set, see Fig. 8. By rotating through all folds, performance metrics are calculated after each iteration, and the results are averaged, providing a comprehensive evaluation of the model's predictive performance.

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}(y_n - \hat{y}_n)^2} \tag{26}$$

$$MAE = \frac{1}{N}\sum_{n=1}^{N}(y_n - \hat{y}_n) \tag{27}$$

$$R^2 = 1 - \sum_{n=1}^{N}(y_n - \hat{y}_n)^2 \Big/ \sum_{n=1}^{N}(y_n - \bar{y}_n)^2 \tag{28}$$

where, y_n is the actual value, $\hat{y}_n$ denotes the predicted value, $\bar{y}_n$ is the mean value.

2.3. AI-based surrogate model for real-time prediction of collision damage

An AI-based surrogate model in this study refers to a computationally efficient approximation model, derived from a trained deep learning framework, that replicates the behavior of complex and resource-intensive numerical simulations. This section details the implementation of an AI-based surrogate model designed for the real-time prediction of collision damage. The process begins with the detection of potential collision scenarios in real conditions using Automatic Identification System (AIS) data, followed by the application of the AI-based model to estimate collision damage dimensions. The accuracy of these predictions is then rigorously validated against detailed simulation results using the super element method, see Fig. 9.

2.3.1. Collision scenarios detection using AIS data

The AIS serves as a critical tool for detecting potential collision scenarios between ships. AIS data provides essential dynamic information, including position, heading, course, speed, and ship type—parameters that are vital for assessing collision risks. An Avoidance Behaviour-based Collision Detection Model (ABCD-M) is proposed to identify potential collision scenarios (Zhang et al., 2021a,b). The detection process involves continuous monitoring and analysis of these parameters to identify possible collision scenarios based on the trajectories of the ships involved. When a potential collision is detected, the method conducts a detailed analysis to evaluate the probability and possible impact of the collision. Collision probabilistic risk can be evaluated by collision risk index estimation method (i.e., Liu et al., 2023; Zhang et al., 2021a,b). The possible collision damage of potential collision scenarios can be evaluated by the AI-based surrogate model

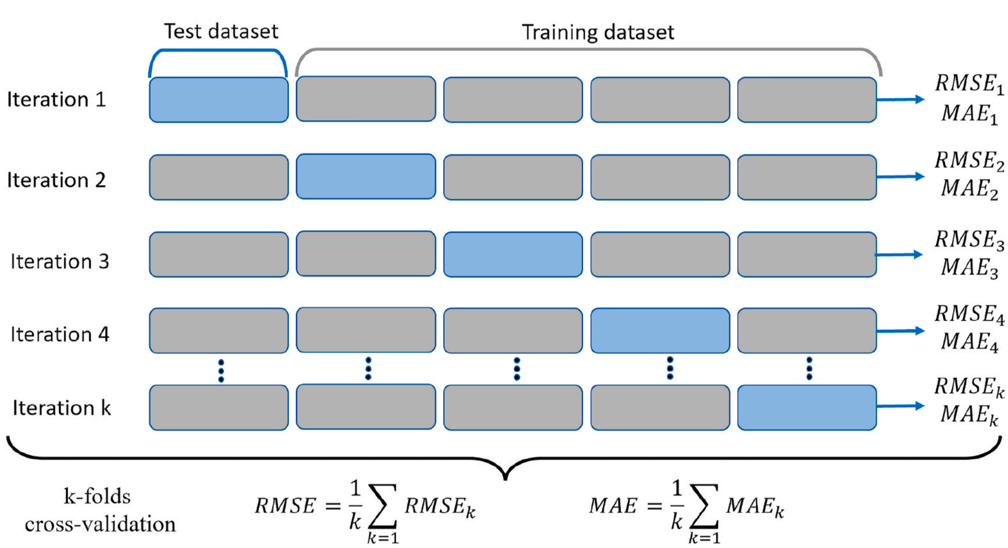


Fig. 8. The k folds cross-validation for model evaluation.

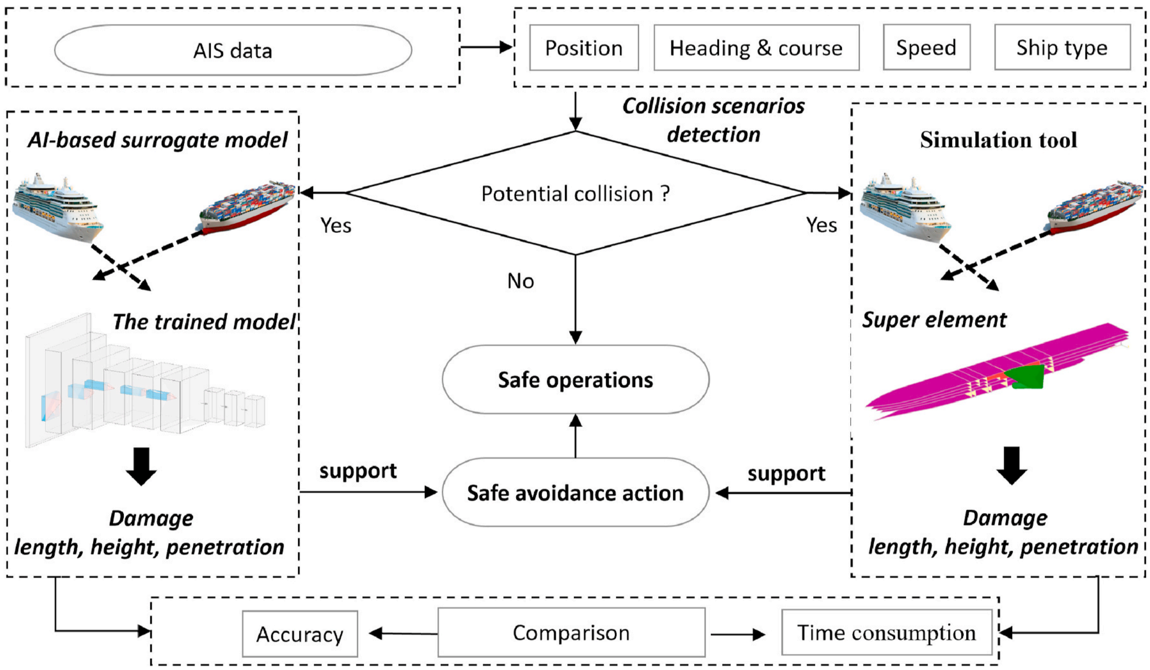


Fig. 9. Applications of the AI-based surrogate model for real-time prediction of collision damage.

developed in Section 2.2. In the absence of any collision risk, the system ensures that safe operations are maintained.

2.3.2. Collision damage prediction using AI-based surrogate model

As shown in Figs. 9 and 10, upon identifying a potential collision scenario using AIS data, the AI-based surrogate model is activated to predict the extent of the resulting damage if no evasive actions of the involved ships are made (Zhang et al., 2021a,b). This model is trained on a comprehensive dataset of collision scenarios (see Section 2.2). It utilizes the identified parameters (e.g. relative position, speed, and ship type) to predict critical damage dimensions, including the length, height, and penetration of the possible collision impact. The model employs advanced deep learning techniques to effectively capture the complex, nonlinear relationships between collision scenarios and the resulting damage. After training, the model is ready for use as a surrogate model. It can predict potential ship collision damage under real conditions, as shown in Fig. 11. This predictive capability provides valuable insights, facilitating informed decision-making for safe avoidance actions and further detailed analyses.

To ensure the robustness and reliability of the AI-based surrogate model, its damage predictions are systematically compared with results generated by a simulation tool. This simulation tool employs the super-element method to model the structural response of ships under collision conditions, producing detailed outputs on damage dimensions such as length, height, and penetration. By juxtaposing the AI model's predictions with these simulation results, the model's accuracy is rigorously validated. This comparison not only affirms the model's predictive performance but also guides further refinements, providing critical insights into the balance between computational efficiency and predictive accuracy, as reflected in the metrics of accuracy, comparison, and time illustrated in Fig. 9.

3. Case study and results

This section presents a case study focused on the Gulf of Finland, specifically addressing the selected struck ship as detailed in Section 2.1.2. It provides an overview of the comprehensive database (dataset 1: simulation dataset) of collision scenarios and the associated damage assessments as detailed in Section 3.1. Additionally, it describes the training and validation process of the deep learning method applied in this context. Furthermore, section 3.3 elaborates on the application of these methodologies to the selected struck ship within the Gulf of

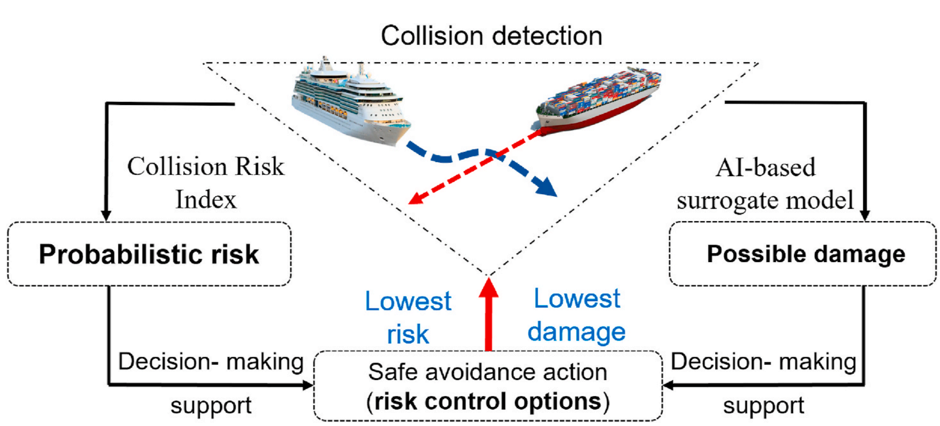


Fig. 10. The diagram of collision scenarios detection for collision risk assessment and decision-making support for collision risk mitigation.

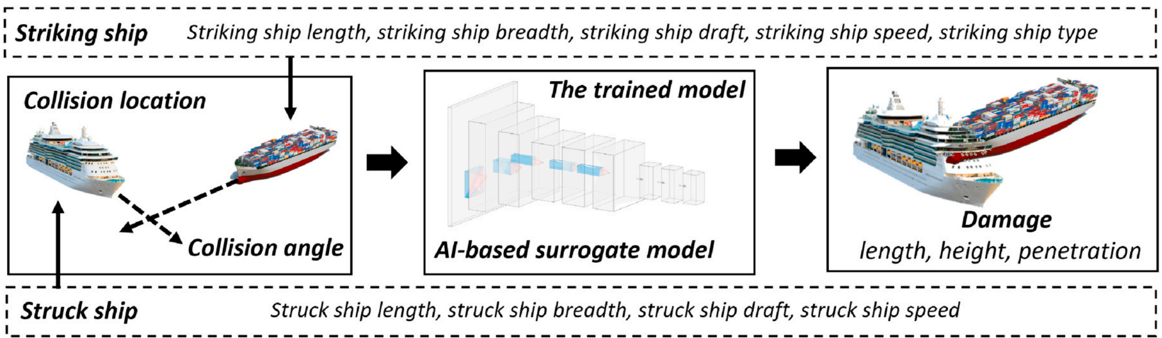


Fig. 11. The diagram of the real time ship collision damage prediction using AI based surrogate model.

Finland (dataset 2: real collision scenarios detected by using AIS data).

3.1. Collision scenarios and associated damages

To create a comprehensive database of collision scenarios and associated damage assessments for developing a ship damage prediction model, various collision scenarios are designed, and the corresponding damages are simulated as follows.

3.1.1. Collision scenarios design

This section introduces the design of collision scenarios (dataset 1) aimed at achieving comprehensive coverage of potential collision events by utilizing quasi-random sequences for variable sampling and stratified sampling techniques (Mauro and Vassalos, 2023). An example of a collision scenario is presented in Fig. 12.

The objective has been to develop a comprehensive set of collision scenarios (dataset 1) that adequately represent the full spectrum of potential ship collision conditions while minimizing the number of simulations required as illustrated in Fig. 12. Fig. 13 presents the distributions of key parameters of collision scenarios in the comprehensive database. The scenarios consider 11 types of striking ship bows, detailed further in Appendix A, and involve the reference ship (Ro-Ro passenger ship). The forward speed of the striking vessel prior to collision is stratified across several discrete levels (e.g., 2, 4, 6, 8, and 10 m/s)/(3.89, 7.78, 11.66, 15.55, and 19.44 kn). The longitudinal position of impact along the reference ship's length is determined using quasi-random sequences to ensure uniform coverage across different potential points of impact between 0.2 L_{pp} and 0.8 L_{pp}. Similarly, the collision angle between the striking and reference ships is sampled using quasi-random sequences to comprehensively cover a range from 20 to 90°. Given that the scenarios focus on mid-ship impacts (0.2–0.8 L_{pp}) with no initial surge velocity for the struck ship, it is deemed unnecessary to calculate the complementary collision angles from 90 to 160°.

The vertical distance between the waterline and the bottom of the ship, accounting for various loading conditions (ship draft), is stratified at multiple levels. By combining stratified and quasi-random sampling techniques, the study efficiently explores the multi-dimensional parameter space defined by these variables. This comprehensive design space ensures that all relevant collision conditions are represented, which is essential for the development of reliable surrogate models for damage estimation.

To reduce computational demands while still generating a robust set of scenarios, 500 quasi-random samples are selected for the longitudinal impact position and collision angle, combined with stratified levels for other variables, resulting in a database of 5500 collision scenarios (500 scenarios per target ship across 11 target ships, see Appendix A), as shown in Fig. 13. This approach balances manageability with sufficient detail to support accurate real-time collision damage prediction.

3.1.2. The associated damages

For each collision scenario, the damage characteristics are obtained through simulations conducted using the SHARP software. These calculations focus on the geometrical attributes of the damage, specifically the damage length (D_L), penetration (D_P), and height ($D_h = z_{UL} - z_{LL}$), as defined by the vertical limits (z_{UL} and z_{LL}). The study encompasses a total of 5500 collision scenarios, designed to ensure a comprehensive representation of the damage space across a wide range of conditions. Of these, 5205 scenarios were successfully simulated, while 295 cases resulted in computational errors, as shown in Fig. 14. The results demonstrate a sufficiently broad distribution across the parameter

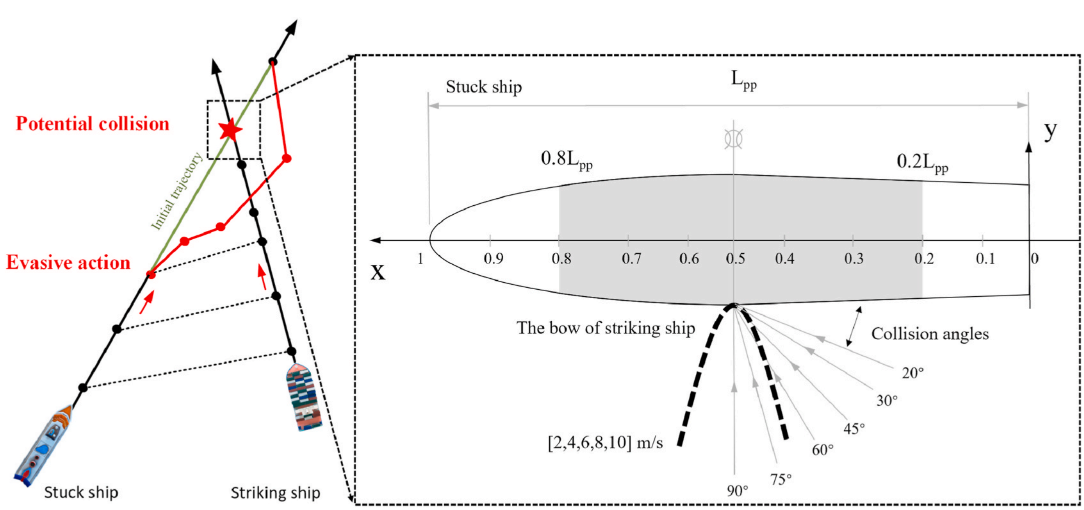
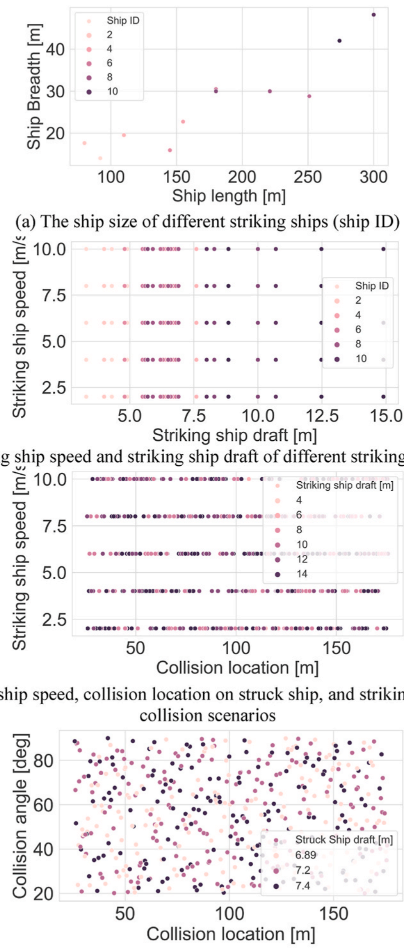


Fig. 12. The diagram of collision scenario.



(a) The ship size of different striking ships (ship ID)

(b) The striking ship speed and striking ship draft of different striking ships (ship ID)

(c) The striking ship speed, collision location on struck ship, and striking ship draft of the collision scenarios

(c) The collision angle, collision location on struck ship, and struck ship draft of the collision scenarios

Fig. 13. The distributions of key parameters of collision scenarios in the comprehensive database.

space, which is conducive to the development of AI-based surrogate models for the real-time prediction of ship damage under diverse conditions. These models have significant potential to enhance the applicability of real-time collision risk assessment tools (Figs. 9 and 10) for onboard use.

Ultimately, this section illustrates that the proposed approach to collision scenario design markedly improves the reliability and efficiency of real-time collision damage prediction models. By contributing a robust database of collision scenarios and corresponding damage assessments, this approach supports the advancement of onboard decision support systems and safety management practices in maritime operations.

3.2. Ship damages prediction using the deep learning method

Based on the comprehensive database of collision scenarios and the associated damage assessments (see Figs. 13 and 14), this section introduces the deep learning methodology for predicting ship damage through a structured process of model training, validation, and testing. A hybrid deep learning model was developed, and after training, an AI-based surrogate for ship damage prediction was established. This surrogate model functions as a predictive tool, leveraging a carefully curated dataset to capture the complex relationships between input parameters and resultant damage. The model's architecture ensures both robustness and generalization, making it well-suited for real-world applications in maritime environments. Its ability to accurately predict ship damage under diverse conditions marks a significant contribution to collision risk assessment and proactive safety management.

To meet the intelligent navigation requirements of ships in real conditions, this section specifies the use of several key input parameters for training the deep learning model. These parameters include the length, breadth, draft, speed, and type of the striking ship, the corresponding characteristics of the struck ship, and the angle of collision. These inputs comprehensively capture the spatial and temporal relationships between the colliding ships. The outputs of the model, consisting of the damage length, damage penetration, and damage height, are used to represent the consequences of ship collisions. Through training and validation, the deep learning model captures the nonlinear relationships between collision scenarios and their outcomes.

The section further details the testing process, where the model's predictive performance is evaluated using a separate dataset to ensure its accuracy in real-world applications. Sensitivity analysis is conducted to assess the impact of variations in input parameters on the model's outputs, thus confirming the model's robustness in capturing the complexities of potential ship collision scenarios. The final trained model serves as an AI-based surrogate that facilitates intelligent decision-making in navigation, contributing to collision avoidance and damage mitigation strategies, see more in Fig. 15.

The paper describes a data partitioning strategy for training, validation, and testing of a deep learning model using a comprehensive database containing 5205 cases. To ensure a robust model development process, 80% of the data is randomly selected from the database using a fixed random state (random_state = seed) to construct the training and validation dataset, while the remaining 20% of the data is reserved as the test set. For the training and validation of the model, the paper employs a 5-fold cross-validation technique on the 80% dataset. This approach involves dividing the training and validation dataset into five equally sized subsets (folds). In each iteration, one-fold is used as the validation set, while the other four folds are used for training the model, as shown in Fig. 8. This procedure is repeated five times, ensuring that each subset serves as the validation set exactly once. Such a method allows the model to be trained and validated on all available data, improving its generalization capabilities.

The test set, which comprises 20% of the original dataset and is not involved in any stage of the model training or cross-validation, is used to assess the final model's performance, see Fig. 17. This provides an unbiased evaluation of the model's predictive accuracy, ensuring its applicability and reliability for real-world scenarios.

To train the proposed LSTM-Transformer model, the architecture described in the paper consists of an input layer, two Long Short-Term Memory (LSTM) layers, each with 32 hidden units, followed by a Transformer Encoder layer with two attention heads, and an output layer. To prevent overfitting and enhance generalization, a layer with a dropout rate of 0.2 is included for regularization. The model is optimized using the QHAdam optimizer (Ma and Yarats, 2018) with an initial learning rate of 0.001, and a cosine learning rate scheduler is applied to dynamically adjust the learning rate throughout the training process. Additionally, for real-time collision consequence prediction, the model operates on a step-by-step basis, accounting for instantaneous changes in collision scenarios in real operational conditions. So, each prediction is made based on the current state, making the prediction step length equal to one. In practice, the time interval for each step aligns with the update frequency of the collision scenarios, ensuring real-time responsiveness to instantaneous changes. The paper employs the DBO algorithm to determine the optimal hyperparameters of the model, such as the number of layers, hidden dimensions, dropout rate, and learning rate. The DBO algorithm is utilized to efficiently search the hyperparameter space, thus identifying the best settings that minimize the MSE during validation. This optimization approach aligns with established practices in hyperparameter tuning, such as grid search methods, and is implemented in conjunction with a 5-fold cross-validation scheme. The effectiveness of this methodology is supported by prior

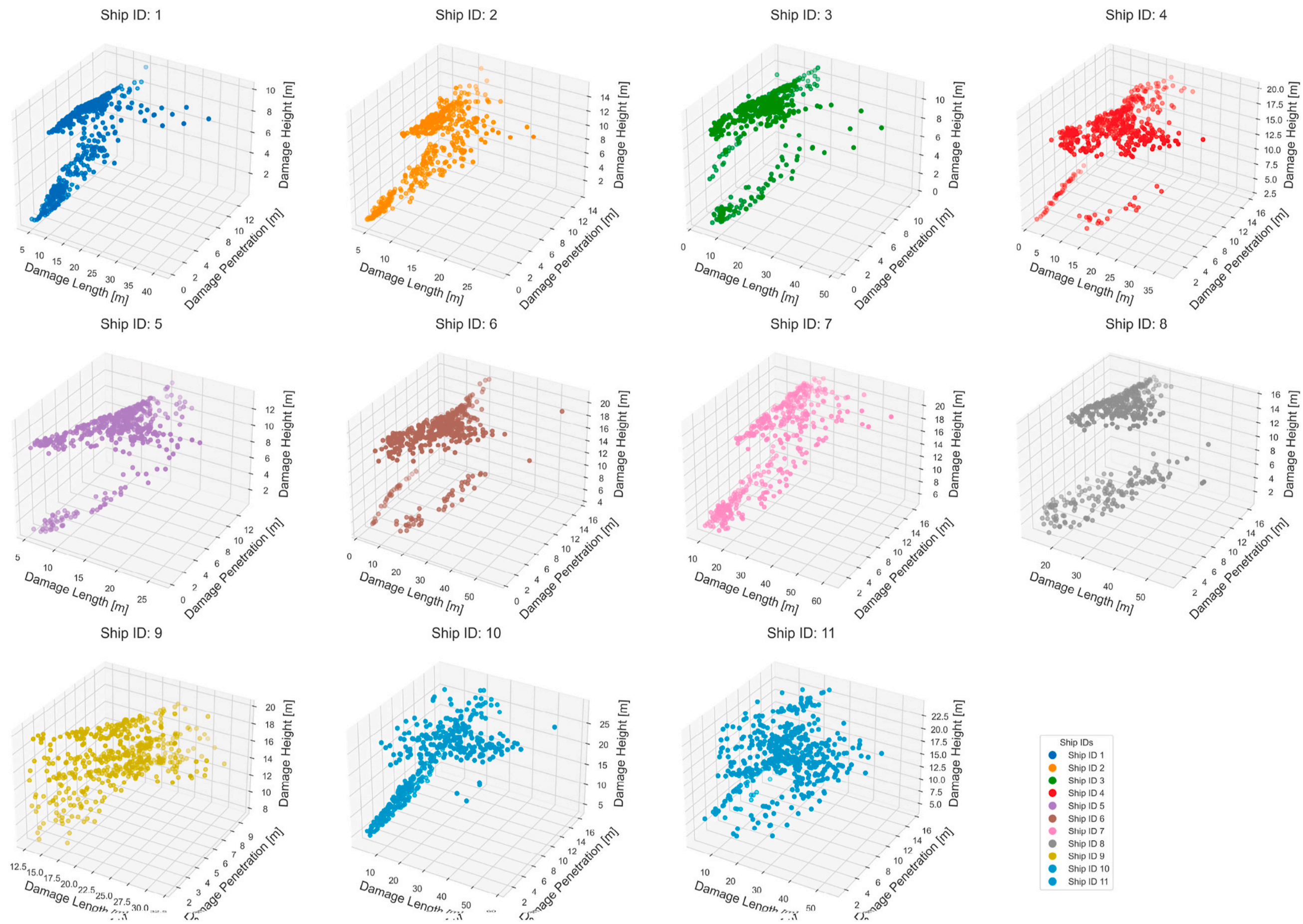


Fig. 14. The distributions of key parameters of associated damages in the comprehensive database.

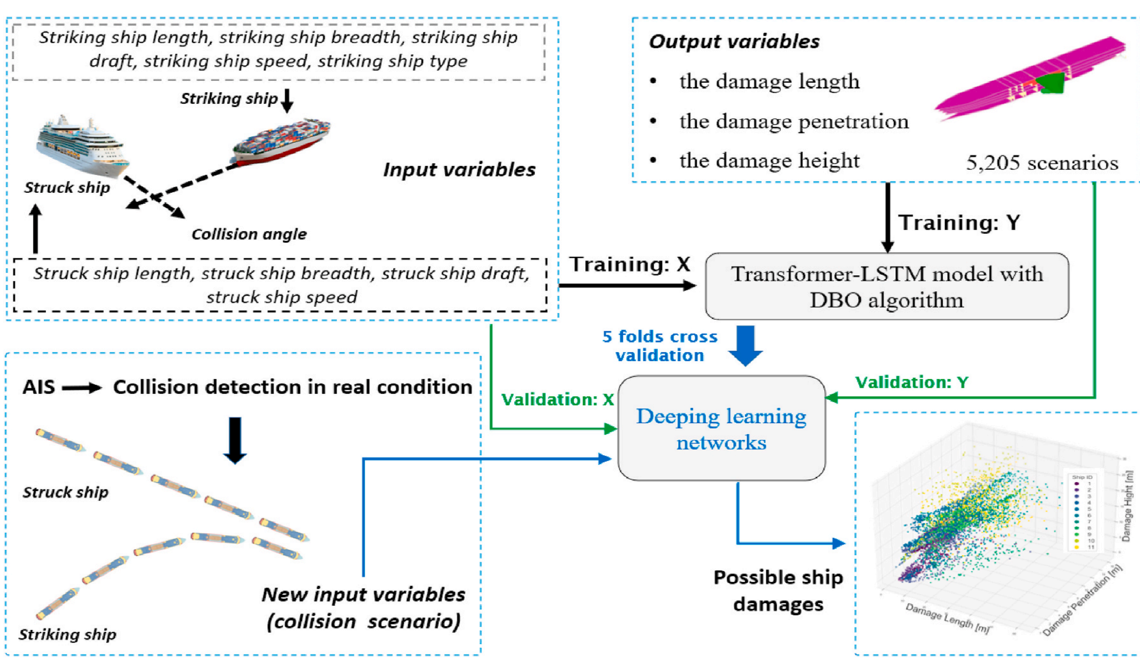


Fig. 15. The deep learning processing of the ship damage prediction for model training, testing and application.

studies (Zhang et al., 2024a,b; Zhang et al., 2025), which have demonstrated the advantages of using cross-validation and advanced optimization techniques to enhance model performance.

The training and validation loss curves in Fig. 16 provide critical insights into the learning dynamics of the proposed LSTM-Transformer model. The curves demonstrate a consistent reduction in both training

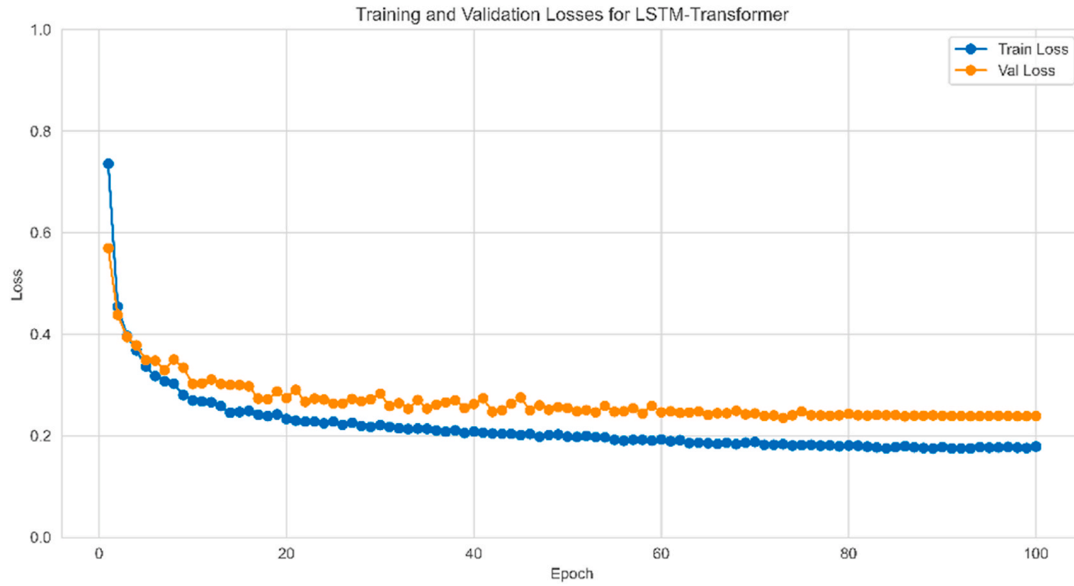


Fig. 16. The model performance evaluation.

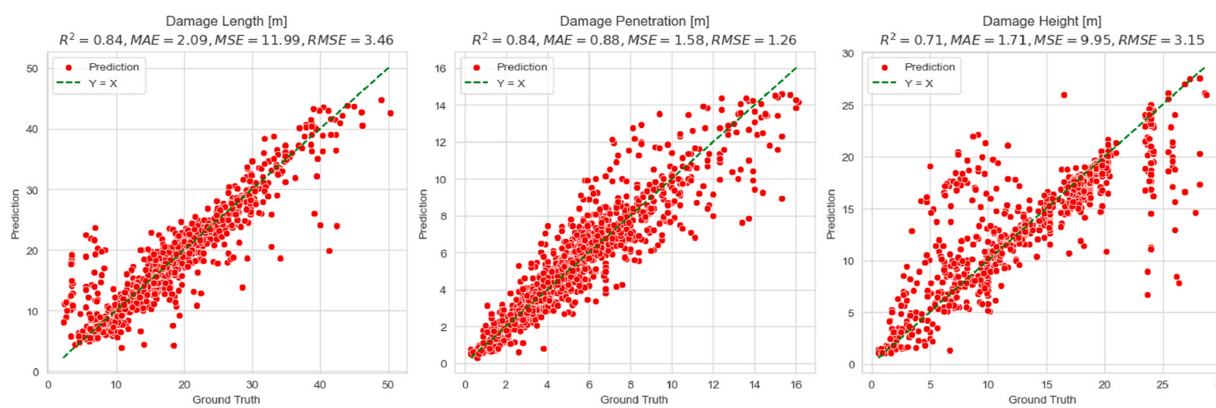


Fig. 17. Model testing results of ship damage prediction based on Transformer-LSTM Model with DBO algorithm optimization.

and validation losses throughout the initial epochs, reflecting the model's ability to progressively learn and adapt to the underlying data patterns. Notably, around the 70th epoch, both losses begin to stabilize, indicating that the model has reached a point where additional training does not significantly enhance its performance on the validation set.

This stabilization is a crucial indicator of the model's optimal fitting. The minimal gap between training and validation losses at this point suggests that the model has struck a balance between underfitting and overfitting. It has effectively learned the relevant features of the training data without becoming overly complex or memorizing specific examples, which would otherwise degrade its generalization ability to new, unseen data.

Furthermore, the convergence of the loss curves suggests that the model architecture, hyperparameters, and optimization strategy (including the use of dropout and the QHAdam optimizer with a cosine learning rate scheduler) have been appropriately tuned. The application of early stopping around the 70th epoch is supported by the lack of significant improvement in validation loss beyond this point, which prevents overfitting and ensures that the model retains a high level of generalizability.

Fig. 17 presents the performance of the trained deep learning model on a randomly selected 20% test dataset (1045 cases). The test results demonstrate the model's ability to accurately predict the three critical damage parameters: damage length, damage penetration, and damage height, each with a high degree of correlation between predicted and ground truth values. The model achieves an R^2 score of 0.84, indicating a strong linear relationship between the predicted and actual damage lengths. The MAE is 2.09 m, while the MSE is 11.99 m^2, and the RMSE is 3.46 m. These metrics confirm that the model can effectively capture the variability in damage length across different collision scenarios, with minimal prediction error. For damage penetration, the model also demonstrates a high degree of accuracy with an R^2 score of 0.84. The MAE is 0.88 m, MSE is 1.58 m^2, and RMSE is 1.26 m. These results indicate that the model can reliably predict the extent of damage penetration, maintaining a low prediction error and closely aligning with the actual observed values. The model's performance in predicting damage height is slightly lower than for damage length and penetration, with an R^2 score of 0.71. The MAE is 1.71 m, MSE is 9.95 m^2, and RMSE is 3.15 m. While there is a reasonable degree of accuracy, the slightly lower R^2 value suggests that the model captures the variations in damage height with less precision compared to the other two damage parameters. However, it still maintains an acceptable level of performance, providing useful predictions for practical applications.

The results illustrate that the deep learning model is effective in predicting ship collision damage outcomes, with strong predictive performance for damage length and penetration and reasonably good performance for damage height. The high R^2 values and low error metrics across all damage types confirm the model's robustness and its capacity to generalize well to new, unseen data, validating its potential for real-world application in damage prediction and maritime safety analysis.

Figs. 18 and 19 present the testing results and sensitivity analysis of the ship damage prediction model for various striking ships, demonstrating the model's ability to predict damage length, damage penetration, and damage height across different collision scenarios.

The model generally performs well in predicting damage length, with most ships showing strong correlations between predicted and actual values, indicated by R^2 values up to 0.95 (e.g., Ship IDs 8, 5, and 2). Most ships have low MAE, MSE, and RMSE values, reflecting accurate predictions in most scenarios.

The model demonstrates robust performance in predicting damage penetration across different ships, with consistent R^2 values ranging from 0.56 to 0.89. Ships like IDs 3, 5, and 7 exhibit high predictive accuracy with low associated errors, confirming the model's reliability in estimating damage penetration.

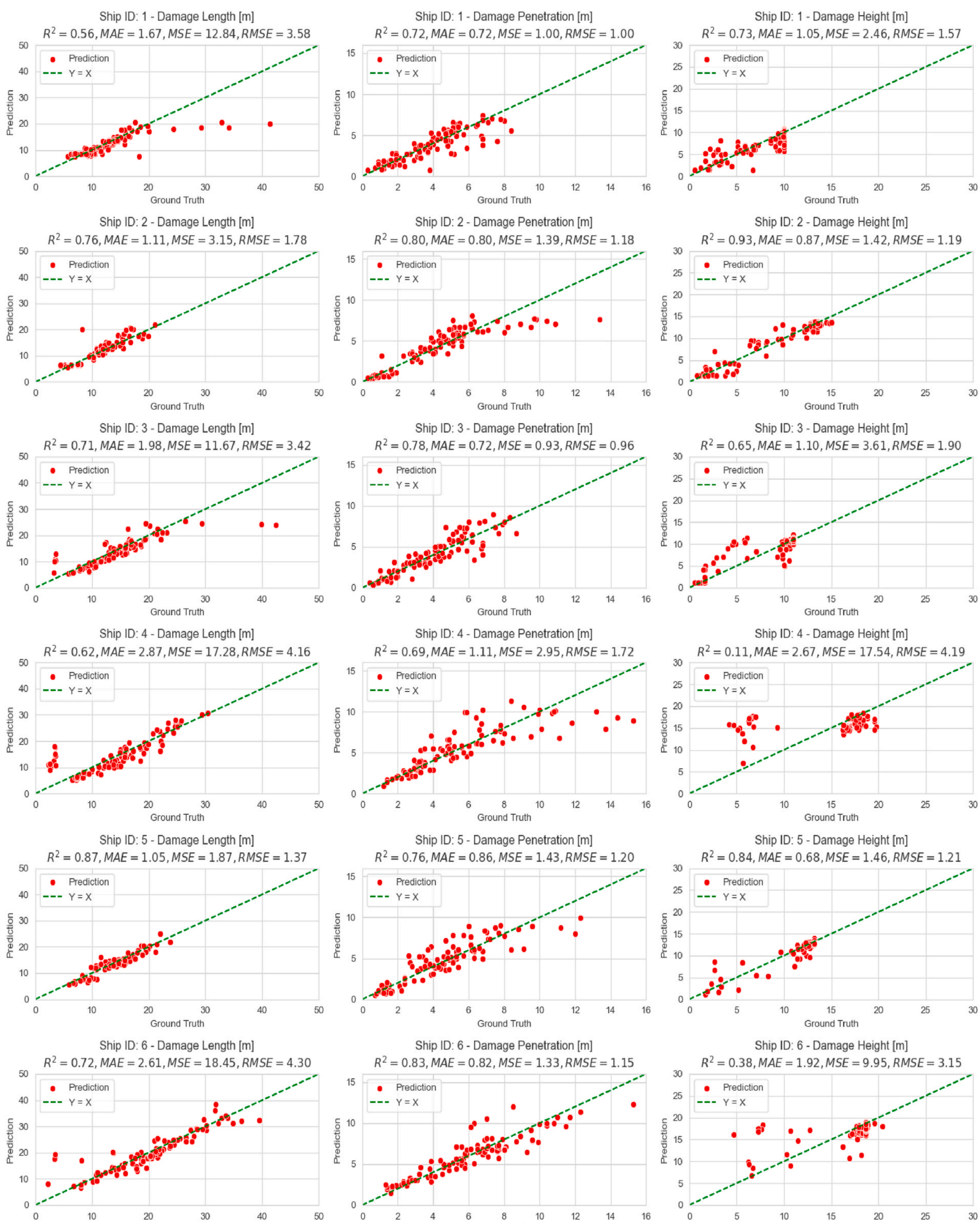


Fig. 18. Model testing results of ship damage prediction for various striking ship (Ship ID 1–6).

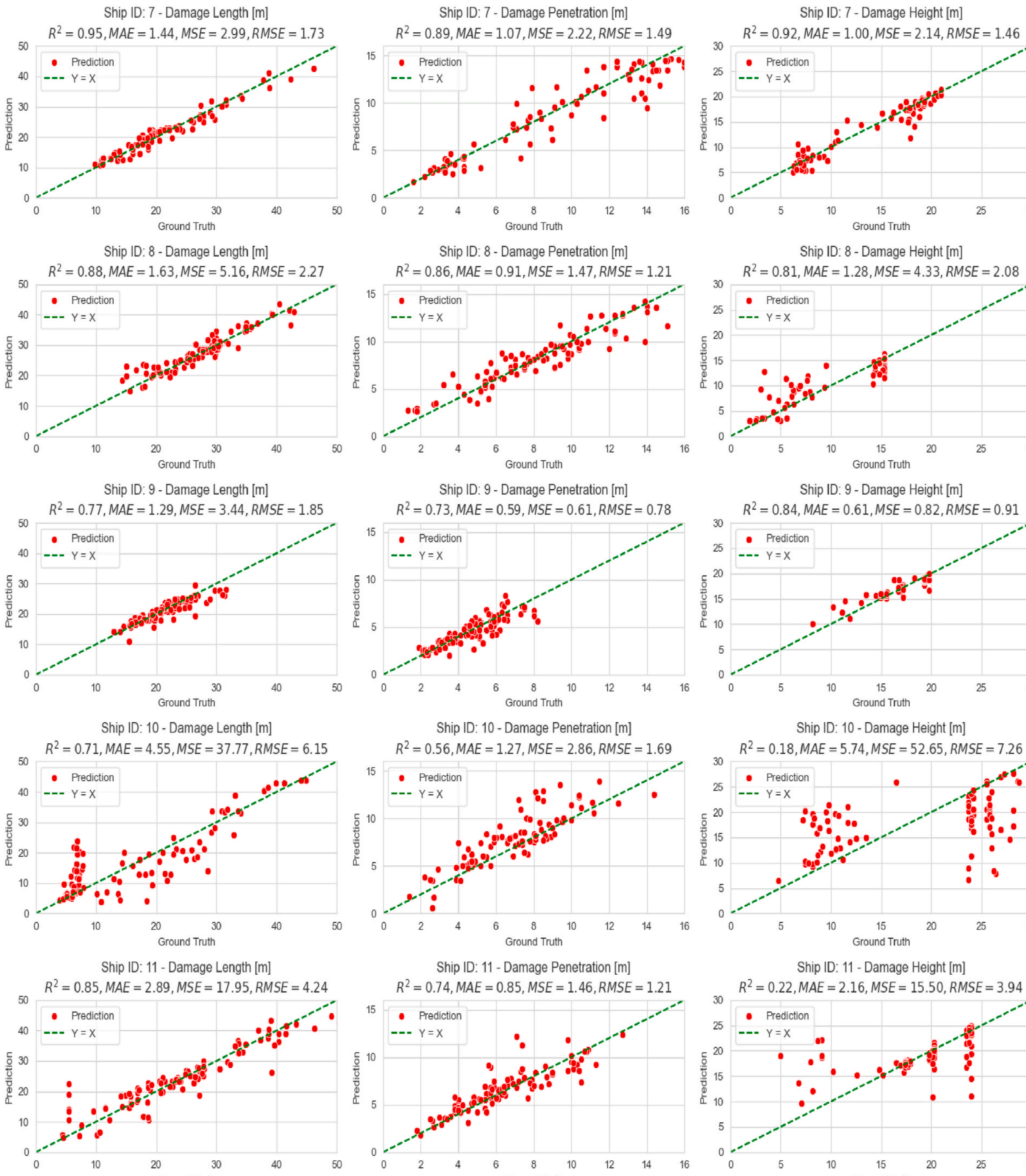


Fig. 19. Model testing results of ship damage prediction for various striking ship (Ship ID 7–11).

The model's ability to predict damage height also shows satisfactory results for several ships, with R^2 values reaching up to 0.92 (e.g., Ship IDs 7 and 8). These results highlight the model's competence in capturing damage height with reasonable accuracy across multiple scenarios.

Overall, Figs. 18 and 19 indicate that the model performs effectively across various striking ship scenarios, with generally strong predictive accuracy for most damage parameters. However, the precision of the predictions varies somewhat across different striking ships, reflecting differences in model performance depending on the specific collision characteristics.

Table 6 presents a comprehensive evaluation of the predictive accuracy of various models for ship damage prediction i.e., MLP, DT, VSM,

Table 6
The accuracy evaluation for the prediction of ship damages using various tools.

Ship damage prediction Model	R^2	MAE (m)	MSE (m^2)	RMSE (m)
LSTM-Transformer model	0.7231	2.1811	3.2742	10.7203
Transformer model	0.7936	1.7052	2.8066	7.8773
MLP model	0.7415	2.0897	3.1366	9.8385
RNN model	0.7797	1.8138	2.8924	8.3662
DT model	0.4872	3.1100	4.6838	21.9381
VSM model	0.5465	3.0414	4.3434	18.8647
LSTM model	0.787	1.7607	2.8365	8.0459
LSTM-Transformer model with DBO algorithm optimization	0.8087	1.5666	2.7088	7.3377

RNN, LSTM, Transformer,LSTM-Transformer, and LSTM-Transformer model with DBO algorithm optimization. The comparison reveals that the LSTM-Transformer model with DBO algorithm optimization achieves the highest performance among all models tested. This model exhibits a superior coefficient of determination, indicating a strong correlation between predicted and actual values. Additionally, it demonstrates the lowest MAE, MSE, and RMSE, reflecting its enhanced capability in minimizing prediction errors.

In contrast, the Transformer model and the LSTM model also show strong performance, with R^2 values of 0.7936 and 0.787, respectively. These models maintain relatively low error metrics, demonstrating their effectiveness in capturing the complex relationships inherent in the ship damage data. However, they fall slightly short of the predictive accuracy achieved by the proposed LSTM-Transformer model with DBO optimization, underscoring the impact of the DBO algorithm in fine-tuning the model's hyperparameters for optimal performance.

Other models, such as the RNN model, and the MLP model, provide moderate predictive accuracy, with acceptable MAE, MSE, and RMSE values, suggesting they are reasonably effective but not at the forefront of performance compared to the proposed model.

Conversely, traditional models like the DT model and the VSM show markedly lower performance. These models are characterized by higher error metrics (e.g., RMSE = 21.9381 m for the DT model), indicating significant limitations in their ability to generalize across the diverse collision scenarios and capture the underlying nonlinear relationships in the data.

Overall, the results from Table 6 clearly demonstrate the advantages of the proposed LSTM-Transformer model with DBO optimization in achieving superior predictive accuracy. This model's robust performance highlights its potential for practical applications in ship damage prediction, offering a more reliable tool than both traditional machine learning models and other deep learning architectures without optimization.

3.3. Generalization evaluation and applications

To validate the generalization capability of the proposed deep learning method, potential collision scenarios (Dataset 2) in the Gulf of Finland were identified using an Avoidance Behavior-based Collision Detection Model (ABCD-M). As described by Zhang et al. (2021a,b), comprehensive research on AIS data processing and synchronization was carried out to ensure the availability of high-quality AIS data for this study. These methods were specifically developed to address challenges such as noise and missing values, providing a reliable foundation for the current analysis.

Using the cleaned AIS data, the ABCD-M detected potential collision scenarios involving struck ships with gross tonnages ranging from 10 000 to 46 124 GT and lengths between 120 m and 218.8 m, covering the year 2029. In total, 3491 potential collision scenarios were initially identified, as illustrated in Fig. 20.

To refine the dataset, a filtering process was applied to exclude striking ships shorter than 50 m, as approximately 90% of these ships had lengths under 33 m, breadths under 10 m, and displacements below 850 tons. Further filtering removed head-on and overtaking scenarios, retaining only crossing collision scenarios (collision angle is more than 20°, see more in Fig. 12). Following this filtering, 1529 collision scenarios were deemed suitable for subsequent crash analysis (dataset 2). The distributions of the striking ship lengths, widths, speeds, and draft after filtering are shown in Fig. 21.

Potential collision scenario is a critical situation that triggers the ship to take evasive action when a collision accident may occur if no evasive action is taken (Zhang et al., 2021a,b). Based on the detected collision scenarios, the paper assumes that the striking ships did not undertake any evasive action. The trained deep learning model (from Section 3.2) was then used to predict the potential collision damage if no evasive action is taken. Notably, this paper assumes that the maximum draft of the ship is 120% of its actual draft. Additionally, to benchmark the predictions of the trained model, the SHARP software was used to simulate the same scenarios. The results of the SHARP simulations were compared with those from the trained model's damage assessment, as depicted in Fig. 22. The results demonstrate that the proposed AI-based surrogate model effectively captures the intricate relationships between ship collision scenarios and the resulting damages, highlighting its strong potential for deployment in real operational conditions. Regarding computational time, the AI-based surrogate model demonstrates significant efficiency advantages, requiring less than 0.1 s per case, compared to several minute per case for the SHARP analysis. Thus, the AI-based surrogate model may offer a crucial tool for real-time estimation of potential collision consequences (damages), enabling rapid decision-making and risk assessment onboard ships.

The generalization evaluation and applications of the AI-based surrogate model to predict collision damages in real scenarios has significant implications for maritime safety management. The model's ability to provide rapid and accurate predictions of collision outcomes allows for timely decision-making and the implementation of risk mitigation measures, such as adjusting ship courses or speeds to avoid potential collisions. This capability is particularly valuable in complex and congested maritime environments where real-time information is essential for ensuring safe navigation. Furthermore, t he model's integration into shipboard decision support systems can enhance situational awareness by providing operators with a reliable tool to assess the potential severity of collisions. This predictive capability supports the proactive management of collision risks, reducing the likelihood of catastrophic outcomes such as ship capsizing, sinking, or severe environmental damage from oil spills.

3.4. Future works

Based on the proposed method for real-time prediction of collision damage consequences, future research will focus on the comprehensive integration of the ship maneuvering prediction model, collision probability prediction model, and collision damage consequence prediction model to enhance onboard intelligent decision-making system adaptability and performance across diverse maritime environments for

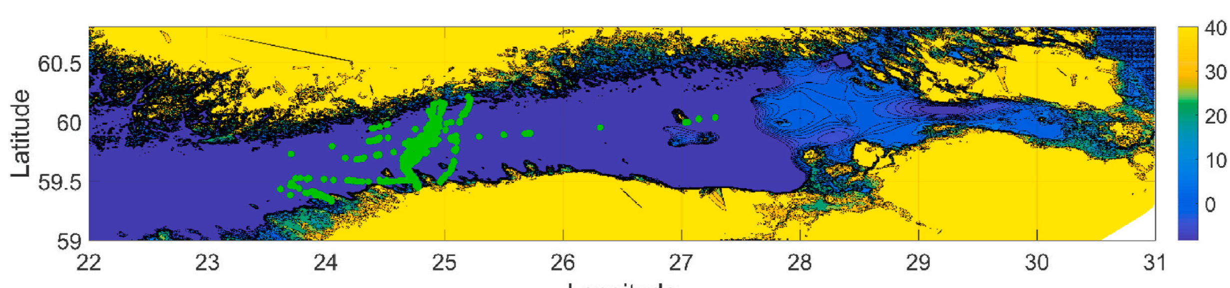


Fig. 20. The locations of the detected potential collision scenarios in the Gulf of Finland.

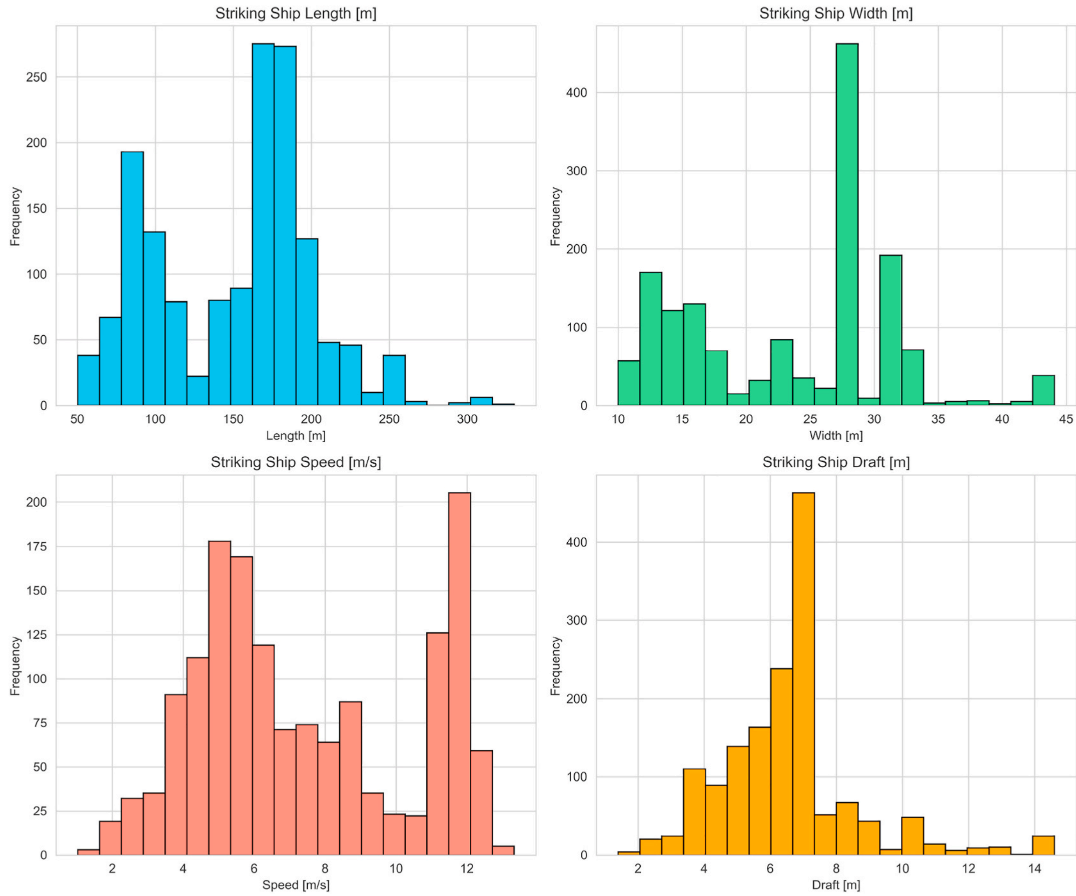


Fig. 21. The distributions of the striking ship lengths, widths, speeds, and draft.

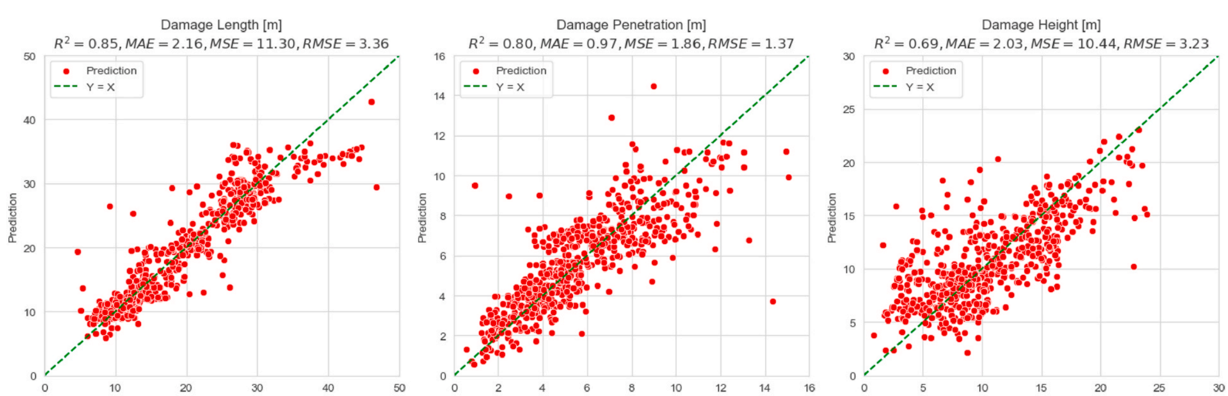


Fig. 22. Comparative analysis of the predicted potential collision damages for detected collision scenarios using an AI-based surrogate model and SHARP simulations.

proactive risk mitigation, as illustrated in Fig. 23. Incorporating real-time environmental and operational data, such as wave, wind, currents, and maritime traffic, will be prioritized to improve prediction accuracy. Advanced ship maneuvering prediction models (Gil et al., 2024; Zhang et al., 2023a) can be further explored by employing hybrid deep learning techniques, enabling the generation of precise and safe maneuvering commands while accounting for complex multi-ship interactions under real-world operational conditions. The integration of these models is expected to yield a robust system capable of accurately predicting collision probabilities and damage consequences based on realistic ship encounter situations at sea (Montewka et al., 2010; Zhang et al., 2021a,b). Furthermore, the integrated model will serve as the foundation for an onboard intelligent decision-making system, specifically designed to manage collision dynamics proactively. This system can be refined to generate and evaluate optimal maneuvering strategies that minimize collision risks and associated damage. Future work will emphasize testing and validating the system in real-world maritime operations, where it can provide predictive insights and proactive ship maneuvering risk management strategies (Zhang et al., 2024a,b; Zhang et al., 2025). Such efforts can ensure the practical applicability of the onboard intelligent decision-making system, delivering real-time decision support that enhances the safety and efficiency of maritime navigation.

In this study, Ro-Pax ships were selected due to their distinct

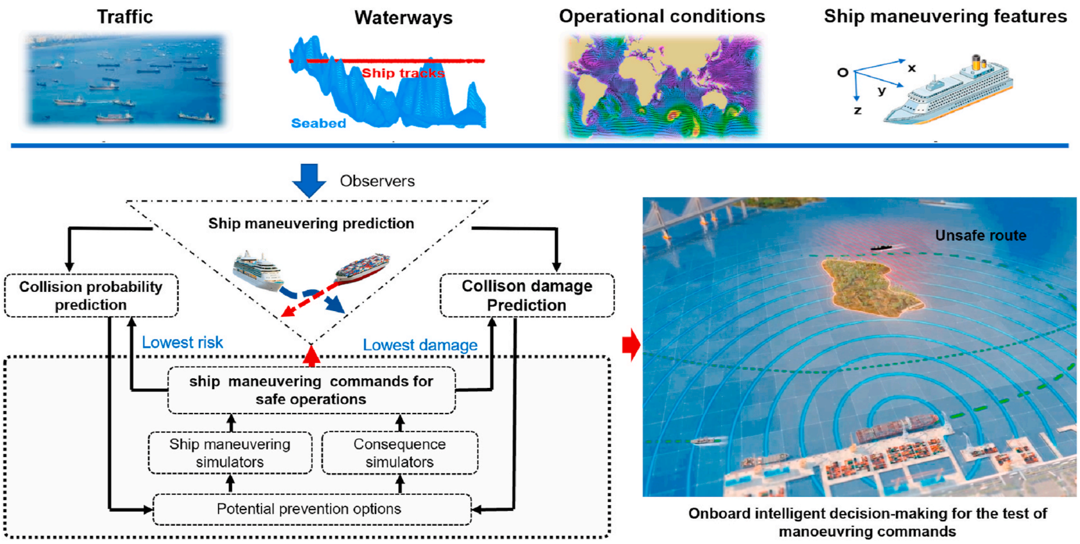


Fig. 23. A flowchart of ship maneuvering control for proactive risk mitigation in the intelligent decision support system.

operational characteristics, structural complexity, and significant safety implications (Montewka et al., 2014). This choice facilitated the demonstration of the proposed method's effectiveness in real shipboard intelligent decision-making applications, particularly in predicting collision damage consequences. However, the framework is not limited to Ro-Pax ships and can be generalized to other vessel types by adapting it to their specific structural and operational features. Future research will focus on expanding the framework's applicability by incorporating additional environmental and operational variables to refine prediction accuracy. Furthermore, collaboration with industry stakeholders and full-scale validation trials will ensure that the proposed system remains reliable, effective, and applicable to a wide range of maritime conditions, contributing to enhanced maritime safety and operational efficiency.

4. Conclusions

This paper presents an innovative deep learning-based framework for real-time prediction of ship collision damages in conditions, addressing a critical gap in current maritime safety management practices. The framework integrates three key components: (1) a comprehensive database of over 5500 collision scenarios and their associated damages, created using the SE method and AIS data; (2) a hybrid deep learning model that combines LSTM networks with Transformer models, optimized through the DBO algorithm; and (3) a validated AI-based surrogate model for real-time damage prediction applied to diverse maritime scenarios. Key findings of this study are summarized as follows.

- The hybrid deep learning model, specifically the LSTM-Transformer model with DBO optimization, demonstrated superior predictive accuracy compared to traditional machine learning and deep learning models. It effectively captured the nonlinear relationships between ship collision scenarios and damage extents, achieving an R^2 value of 0.81 and low error metrics across multiple damage parameters.
- The model's validation through extensive k-fold cross-validation and generalization tests confirmed its robustness and reliability in predicting collision damages across a wide range of scenarios. This capability was further supported by its successful application to real collision scenarios detected in the Gulf of Finland, where it accurately predicted collision damage outcomes with significant computational efficiency compared to conventional simulation methods.
- The proposed AI-based surrogate model may offer a promising tool for real-time maritime safety management. It enables rapid estimation of collision consequences, facilitating proactive decision-making and risk mitigation measures, which are crucial for maintaining safe navigation in complex and congested maritime environments.

In conclusion, the integration of advanced deep learning techniques and optimization algorithms, as demonstrated in this study, represents a significant advancement in maritime collision risk assessment. The proposed framework not only enhances the accuracy and efficiency of damage predictions but also contributes to the development of intelligent decision support systems for real-time operational safety.

CRediT authorship contribution statement

Mingyang Zhang: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Hongdong Wang:** Writing – review & editing, Software, Investigation, Conceptualization, Data curation. **Fabien Conti:** Writing – review & editing, Data curation. **Teemu Manderbacka:** Writing – review & editing. **Heikki Remes:** Writing – review & editing, Supervision. **Spyros Hirdaris:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

We declare that we have no financial and personal relationships with other people or organizations that can inappropriately influence our work, there is no professional or other personal interest of any nature or kind in any product, service and/or company that could be construed as influencing the position presented in, or the review of, the manuscript entitled, '*A hybrid deep learning method for the real-time prediction of collision damage consequences in real conditions*'.

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Special recognition is given to CSC Finland for granting access to their parallel computing facilities. The opinions expressed in this paper are solely those of the authors and do not necessarily represent the perspectives of the sponsors.

Appendix A

Table A1
The modelled striking ships bow shapes.

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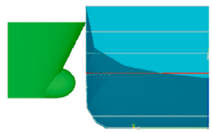
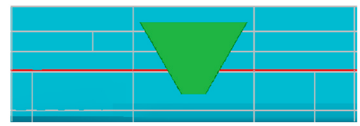
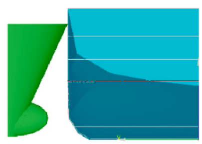
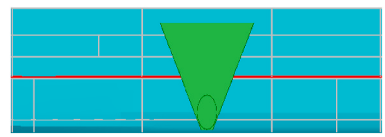
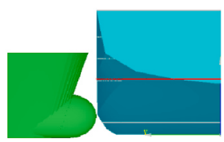
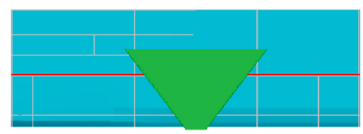
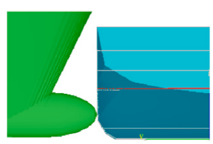
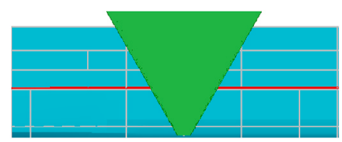
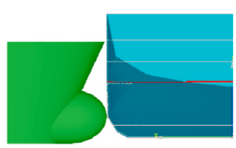
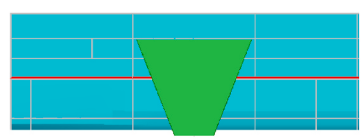
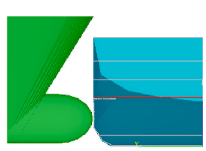
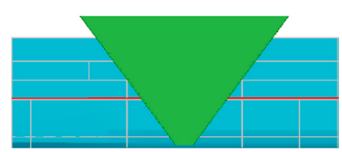
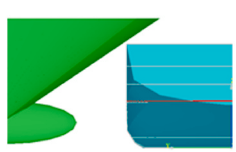
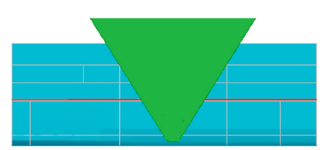
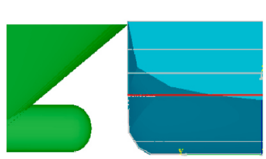
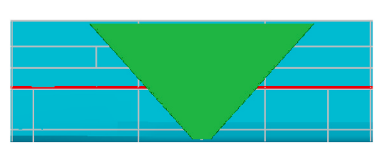
1		
2		
3		
4		
5		
6		
7		
8		

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Table A1 (*continued*)

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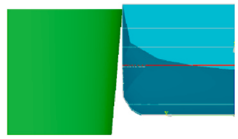
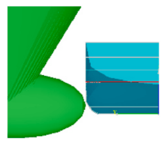
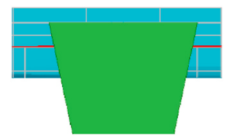
9		
10		
11		

Data availability

Data will be made available on request.

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