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Damage surrogate models for real-time flooding risk assessment of passenger ships

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ABSTRACT

Real-time assessment of flooding risk associated with the collision between two ships, requires a fast estimation of damage dimensions and associated survivability. The state-of-the-art frameworks for risk assessment on passenger ships do not consider a direct evaluation of damages through crash simulations but refer to probabilistic considerations, modelling damage characteristics according to statutory marginal distributions of damage breaches too old to be any longer relevant. In any case, such an approach is not possible for the real-time risk assessment process developed in project FLARE, aimed at promoting the employment of first-principles tools for risk evaluation. In this spirit, the present work investigates the possibility of developing a database-oriented damage breach model, which employs direct crash analyses with the super-element code SHARP. However, the sole usage of crash simulations is not suitable for real-time applications. Therefore, starting from the collision simulation database, surrogate models have to be derived for real-time application. In this specific case, three different strategies have been used for the models creation namely: multiple linear regressions, neural networks and decision trees. Here, the strategy to build the database and application on a reference passenger ship is described, highlighting the differences in accuracy and calculation time between the proposed surrogate models.

1. Introduction

The quantification of risk onboard passenger ships is a topic of primary importance for the safety of all the people onboard before and after an accident occurred. In particular, when the hazard implies flooding of the vessel, consequences may be catastrophic, leading to the possibility of an immediate capsize of the vessel with consequent loss of all the people onboard. For such a reason, assumptions and simplifications usually employed in assessing risk at the design phase are unsuitable for an instantaneous real-time screening during the vessel operation. In this sense, the path laid by Project FLARE (2023) suggests a more consistent and rational application of first-principles calculations for the assessment of flooding risk. This implies the adoption of time-domain simulations for the vulnerability assessment, advanced evacuation analysis to determine the time to evacuate and crash simulations for determining the damage breach dimensions. Such an approach gives crash analyses a role of primary importance in determining the necessary inputs to flooding analyses, providing higher reliability compared to the statutory probabilistic distributions of antiquated damage breach characteristics.

The present work focuses on the generation of damages, not for the execution of damage stability calculations but for the generation of surrogate models to be employed for an onboard flooding risk assessment. As highlighted in previous studies, the execution of crash analyses requires a computational effort not suitable for real-time calculations, both using FEM (Finite Element Method) or super-elements software. However, such simulations are useful for generating suitable databases of collision cases, describing breach dimensions as a function of specific parameters of the striking and struck vessels. Once a fast description is available for the damage location and dimensions, the risk of flooding and the consequences of that event can be assessed by estimating the Potential Loss of Life (*PLL*) in real-time.

As the creation of a collision breaches database for surrogate model generation requires a large number of calculations, the super-element method presents a good balance between the simulation accuracy and the total calculation time. This allows for developing a database with

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Nomenclature

α_c	Collision angle
μ	Mean of an aleatory variable
σ	Standard deviation of an aleatory variable
B_D	Damage penetration
B_s	Ship breadth
c	Damage scenario consequences
FR	Fatality rate
H_D	Damage height
I_{side}	Functional of the damaged side
L_D	Damage length
L_s	Ship length
p	Probability density function
PLL	Potential Loss of Life
POB	People on board
s	Survivability
T_s	Ship draught
T_{strik}	Striking ship draught
T_{struk}	Struk ship draught
TTC	Time to Capsize
TTE	Time to Evacuate
V_s	Ship speed
V_{strik}	Striking ship speed
V_T	Target ship speed
x_D	Longitudinal position of the damage centre
z_{LL}	Damage vertical lower limit
z_{UP}	Damage vertical upper limit
AIS	Automatic Identification System
DOE	Design of Experiments
DSS	Decision Support System
FEM	Finite Element Method
FLARE	FLooding Accident REsponse
GPS	Global Positioning System
SOLAS	Safety Of Life At Sea

design of experiments (DOE) techniques resulting in more than 5000 collision cases, thus suitable for applying regression techniques for surrogate model determination.

In addressing this requirement, the following main topics are covered by this paper.

- Determination of a methodology for fast damage dimension estimation compatible with the real-time flooding risk assessment framework developed in project FLARE.
- Creation of a database of collisions with direct calculations.
- Development of surrogate models for damage dimensions employing three different techniques: multiple linear regressions, neural network, and forest tree.
- Comparison of the three regression strategies for real-time application.

To address the aforementioned points, the paper has been structured as follows. After a short introduction on the state-of-the-art in risk assessment for passenger ships, Section 3 describes the flooding risk assessment in real-time for onboard applications. Section 4 details the crash analyses with the super-element method, with a focus on the software SHARP (Le Sourne et al., 2012). Section 5 demonstrates the process and methods adopted to generate the database of collisions, and Section 6 describes the methodology employed to develop the surrogate models for damage dimensions. Finally, Section 7 gives an example of the applicability of the three surrogate models in real-time. Throughout the paper, all the developments are supported by an application example on a reference cruise ship, described in Section 3.

2. State-of-the-art on risk assessment for passenger ships

The risk assessment for passenger ships is a topic covering multiple aspects related to different kinds of hazards (Gil et al., 2020; Wang et al., 2021). Therefore, numerous strategies and approaches to risk have been followed and developed. The techniques related to risk follow two main streams: the risk evaluation before an accident occurs and the risk after an accident. Most of the studies cover the risk assessment after the accident occurs. In such cases, the risk deals with onboard flooding (Ventikos et al., 2023) or fire events (Spyrou and Koromila, 2020). The main problem with these analyses concerns ship evacuation, addressed through dedicated evacuation studies (Wang et al., 2023). Once the risk before an accident needs to be studied, the problem of possible collisions or groundings is addressed by associating the risk of a hazard with the susceptibility of the ship to the selected danger (Montewka et al., 2014). In such a case, the study analyses possible routes for the vessel, estimating the possibility of having an accident due to traffic and pathway complexity (Taimuri et al., 2023). Such analyses are general and do not estimate the consequences of the possible accident. Some authors enhanced this concept by modelling the consequences through indices associated with static analyses of the damaged ship (Ruponen et al., 2022).

A different way to approach the risk evaluation before an accident consists of predicting the consequences of the hazard through direct calculations, employing first principle tools for the analyses. However, first principle tools require high computational effort and time; thus, they are not suitable for real-time applications. The present work deals with real-time risk evaluation before an accident, more precisely before a ship-to-ship collision. In this sense, the main issue is finding a methodology that provides results in real-time, offering higher reliability than the available approaches based on simplified calculations.

As highlighted in Vassalos et al. (2023), the adoption of surrogate models derived from first-principles calculation is an approach that allows for real-time estimation of risk, thus suitable for onboard applications. The process employs the Potential Loss of Life (PLL) as a metric for risk, evaluating the PLL in three steps: damage modelling, survivability and consequences of the accidents. The following section elaborates these three steps. However, the main focus of the study is on real-time damage generation, providing, for the first time, a method to estimate the location and dimensions of a potential breach. The process employs a database of direct crash analyses as a starting point to develop surrogate models for real-time prediction of breach dimensions.

3. Real-time flooding risk assessment

Before delving into the process for the development of surrogate models and crash analyses, it is worthy to provide a brief description of the framework for onboard real-time risk assessment for passenger ships. The real-time risk assessment onboard passenger ships (or ships in general) requires the execution of the following main actions.

- Identification of potential hazards.
- Evaluation of the risk associated with the detected danger.
- (optional) Provision of countermeasures to reduce the evaluated risk.

The last item is optional as it is relevant for an onboard Decision Support System (DSS), which is not in the scope of the present work. Furthermore, it is necessary to distinguish between evaluating risk before and after the accident. The present work refers to a framework for

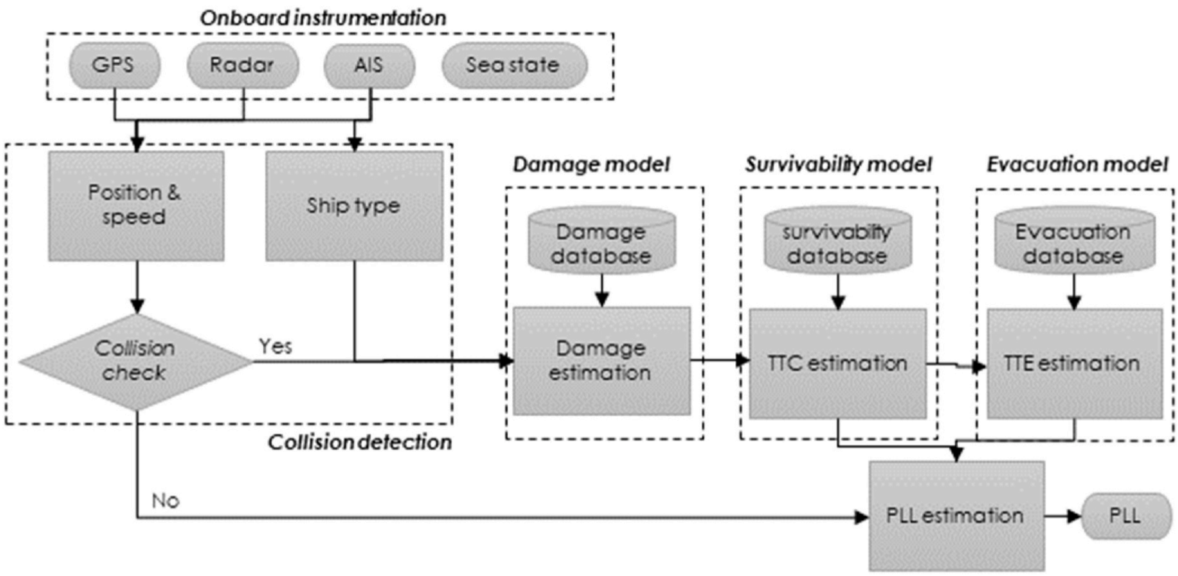

Fig. 1. Process for onboard real-time flooding risk assessment.

real-time risk estimation for potential future collisions before the accident occurred. For this phase, the main focus is on the crash analysis and flooding simulations, whilst for the after-accident phase the focus is more centred on evacuation analyses. As such, the before-accident framework for risk assessment is built with a multi-level approach, providing different approximations according to the data and tools available for the crash, survivability, and evacuation analyses. Fig. 1 gives an overview of the real-time framework for flooding risk assessment, while the next sections describe the process necessary to develop an onboard risk estimation tool pursuing the path of a multi-level approach, whilst considering the enhancement provided by several studies within the FLARE project.

3.1. Multi-level risk metric

The flooding risk assessment is a topic of interest for the operational phase of a passenger ship. Generally, conventional methods employ the concept of susceptibility and vulnerability to an accident to evaluate such risk (Montewka et al., 2021; Ruponen et al., 2022). However, aiming at a determination of risk in real-time, it is better to evaluate flooding risk through the Potential Loss of Life *PLL*, which has the following definition:

$$PLL = p_f \cdot c_f \tag{1}$$

where p_f is the probability of flooding and c_f defines the consequences of the associated flooding event. In a calculation framework, *PLL* according to equation (1) is an attained risk level, to be compared with a required reference value representative of a tolerable/acceptable risk threshold.

The p_f incorporates multiple aspects describing or associated with the flooding event. Therefore, it is convenient to rewrite equation (1) splitting p_f in multiple independent probabilities:

$$PLL = \sum_{i=1}^{N_{hz}} \sum_{j=1}^{N_{op}} \sum_{k=1}^{N_{ld}} \sum_{h=1}^{N_c} p_{hz_i} p_{op_j} p_{ld_k} p^*_{c_h} \left(1 - s_{c_h}\right) \cdot c_{f_{i,j,k,h}} \tag{2}$$

where N_{hz} is the number of possible hazards, N_{op} is the number of operational areas, N_{ld} is the number of loading conditions and N_c is the number of flooding cases. In equation (2), the probability associated with the flooding case is split into the case occurrence p_c* and the survivability s_c to the associated flooding case, as is usual in damage stability (Vassalos et al., 2022a). Such a formulation derives from the design phase risk framework developed in the FLARE project (Vassalos et al., 2022b). However, some of the terms in the equation are not needed for real-time calculations; thus, the real-time *PLL* can be reduced to the contribution given by the survivability of an event and its associated consequences (Vassalos et al., 2023), which means $PLL = (1\text{-}s)c_f$. Therefore, it is necessary to describe c_f in higher detail, according to the following formulation:

$$c_{f_{i,j,k,h}} = FR_{i,j,k,h} \cdot POB_{i,j,k,h} \tag{3}$$

where *FR* is the fatality rate and *POB* is the number of people onboard. Hence, the determination of the *PLL* requires knowledge of survivability sc and fatality rate FR; thus, aiming at using first-principles calculations, necessitates the execution of time-domain flooding simulations in an open sea and advanced evacuation analyses (Vassalos et al., 2022b, 2022c). However, survivability and evacuation analyses can be executed with different approximations, realising different fidelity levels (Vassalos et al., 2022d).

The multi-level framework defined in the FLARE project distinguishes between two levels of fidelity for the survivability analyses. Level-1 employs static or quasi-static analyses, while Level-2 uses rigid-body time-domain simulations. Relating to Level-2, two additional options are available for a complete risk assessment: Level-2.1 and Level-2.2, respectively. These two options differ in the assumptions taken for the fatality rate *FR* evaluation. Level-2.2 employs complete evacuation analyses, while Level 2.1 uses the following approximated function for *FR* estimation:

$$FR = \begin{cases} 0.0 & if\ TTC > n \\ 0.8\left(1 - \dfrac{TTC - 30}{n - 30}\right) & if\ 30 \leq TTC \leq n \\ 1.0 & if\ TTC < n \end{cases} \tag{4}$$

where *TTC* is the time to capsize assessed through the flooding simulations and *n* is the maximum allowable evacuation time in seconds according to MSC.1/Circ. 1533 (IMO, 2016).

The assumption provided by equation (4) neglects the usage of evacuation analyses. However, a study within the FLARE project highlights how Level-2.1 and Level-2.2 produce comparable results on a set of reference passenger ships (Cardinale et al., 2022; Vassalos et al., 2022c). For such a reason, the framework for real-time risk assessment can be implemented at Level-2.1, which means employing time-domain simulations for flooding and equation (4) for the evaluation of the fatality rate.

Table 1
Input needed for an onboard real-time flooding risk assessment.

Input name	Unit	Instrumentation
Ship latitude	deg	GPS
Ship longitude	deg	GPS
Ship speed	kn	GPS or onboard computer
Ship heading	deg	GPS or onboard compass
Target[a] latitude	deg	GPS, AIS or Radar
Target longitude	deg	GPS, AIS or Radar
Target speed	kn	GPS, AIS or onboard computer
Target heading	deg	GPS, AIS or Radar
Target ship type	–	AIS
Target ship length	m	AIS
Target ship breadth	m	AIS
Target ship draught	m	AIS
Significant wave height	m	Wave radar, motions or statistics

[a] Target ship refers to a potential striking ship.

Table 2
Reference ship main particulars.

Characteristic	Symbol	Value	Unit
Length between perpendiculars	L_{PP}	216.8	m
Length overall	L_{OA}	238.0	m
Breadth moulded	B	32.2	m
Depth	D	16.0	m
Design draught	T_S	7.2	m
Displacement	Δ	33923	ton
Centre of gravity height	KG	15.1	m
No. of Passengers	N_P	1800	–
No. of crew members	N_C	600	–

3.2. Real-time risk

The above-described methodology to evaluate the risk through the *PLL* is necessary but not sufficient to perform a real-time risk assessment for ship-to-ship collisions for onboard use. In fact, the first step for such a tool is to detect potential hazards, using data available from the onboard instruments (GPS, AIS, Radar, etc.). This means estimating the route, speed, and main dimensions of all potential striking ships within a certain distance from the reference ship. Besides, the tool needs an estimate of the environmental conditions, provided by onboard instrumentation or from weather data available from local agencies/stations. Subsequently, there is the need to estimate the future path of the target (potential striking) ships, evaluating the most probable collision point, speed, and collision angle in case of a future impact with the reference ship.

The described actions can be accomplished by employing different levels of simplifications. As an example, the estimation of the route can be performed by analysing consecutive interrogations of GPS, Radar or AIS data, evaluating the future position of an object based on its actual position, heading, and speed. Furthermore, the possibility to have multiple sources of input data allows for mitigating the potential presence of missing inputs, as, especially for AIS sources, the data flow may not be continuous (Montewka et al., 2021). Table 1 provides the list of inputs needed by the onboard tool for real-time flooding risk assessment together with the associated data source.

However, the multiple sources of inputs together with possible missing/incongruent data or measuring errors lead to uncertainties in the inputs read by the risk assessment tool. The appropriate modelling of such errors or uncertainties requires the knowledge of all instruments, sensors, and measuring systems mounted onboard. Hence, with this knowledge being unavailable within the FLARE project, a general Gaussian model is considered, sufficiently general to be further developed and extended in subsequent more focused studies. Therefore, according to the adopted assumptions, the measurements uncertainties assume the following form:

$$p(x_i) = \frac{1}{2\pi\sigma_i} e^{-\frac{1}{2}\left(\frac{x_i-\mu_i}{\sigma_i}\right)^2} \tag{5}$$

where μ_i is the signal provided by the considered sensor/instrument (interpreted as the mean value of a Gaussian process) and σ_i is the standard deviation used to simulate uncertainties.

With the introduction of uncertainties, the determination of PLL should be reformulated to consider the peculiarities associated with introducing a probabilistic distribution as per equation (5). In fact, according to the general diagram provided in Fig. 1, the input data and associated uncertainties enter the damage model, which estimates the damage dimensions. Therefore, with the input being formed by distributions (due to uncertainties modelling), the damage output is also composed of distributions.

Subsequently, the outputs of the damage model provide input for the *PLL* evaluation. Following a Level-2.1 model, the *PLL* is evaluated in two steps; first, the *TTC* is estimated from a surrogate model generated by a database of time-domain simulations composed of critical flooding scenarios for the struck ship (Mauro et al., 2022a, 2022b). Then, equation (4) is applied to each member of the *TTC* distribution generated by the survivability model, which means obtaining a *PLL* distribution. The final real-time *PLL* value is then determined as a Quasi-Monte Carlo integration process on a sample of input values. Then the *PLL* results from the following integration formula:

$$PLL \approx \frac{1}{N_{QMC}} \sum_{i=1}^{N_{QMC}} PLL_i(x_{D_i}, V_{T_i}, \alpha_{c_i}) \tag{6}$$

where x_D is the longitudinal position of the breach centre, V_T is the target ship speed, α_c is the collision angle and N_{QMC} is the number of quasi-random samples.

The present work focuses on the damage model and its generation through direct collision simulations, obtaining a data source for the development of a fast surrogate model for real-time calculations. Therefore, the characteristics of the model are discussed in the following sections, together with the description of the crash analysis tool employed to develop the damages database. The description of the process is supported by examples on a reference ship described hereafter.

3.3. Reference ship

A reference case is provided, that of a sample cruise vessel to describe the novel approach for database generation employing direct crash analyses and real-time damage dimensions estimation. This reference ship has been used during benchmarking activities in project FLARE (Kim et al., 2022) but was already employed during the FLOODSTAND (2012) project (Luhmann, 2009). Table 2 provides the main particulars of the ship, while Fig. 2 shows its general arrangement.

4. Crash analyses with super-elements method

Crash analyses can be handled with different approximations, starting from high-fidelity methods like FEM simulations down to simple empirical formulations. As a matter of fact, the higher the accuracy is, the longer the computational demand becomes. Therefore, aiming at performing a very large number of calculations, the right balance between accuracy and computational effort needs to be found. To this end, a suitable solution is given by the super-elements method. Here, the computational method is briefly discussed together with the resulting damage model that can be used for the generation of a damage breach database.

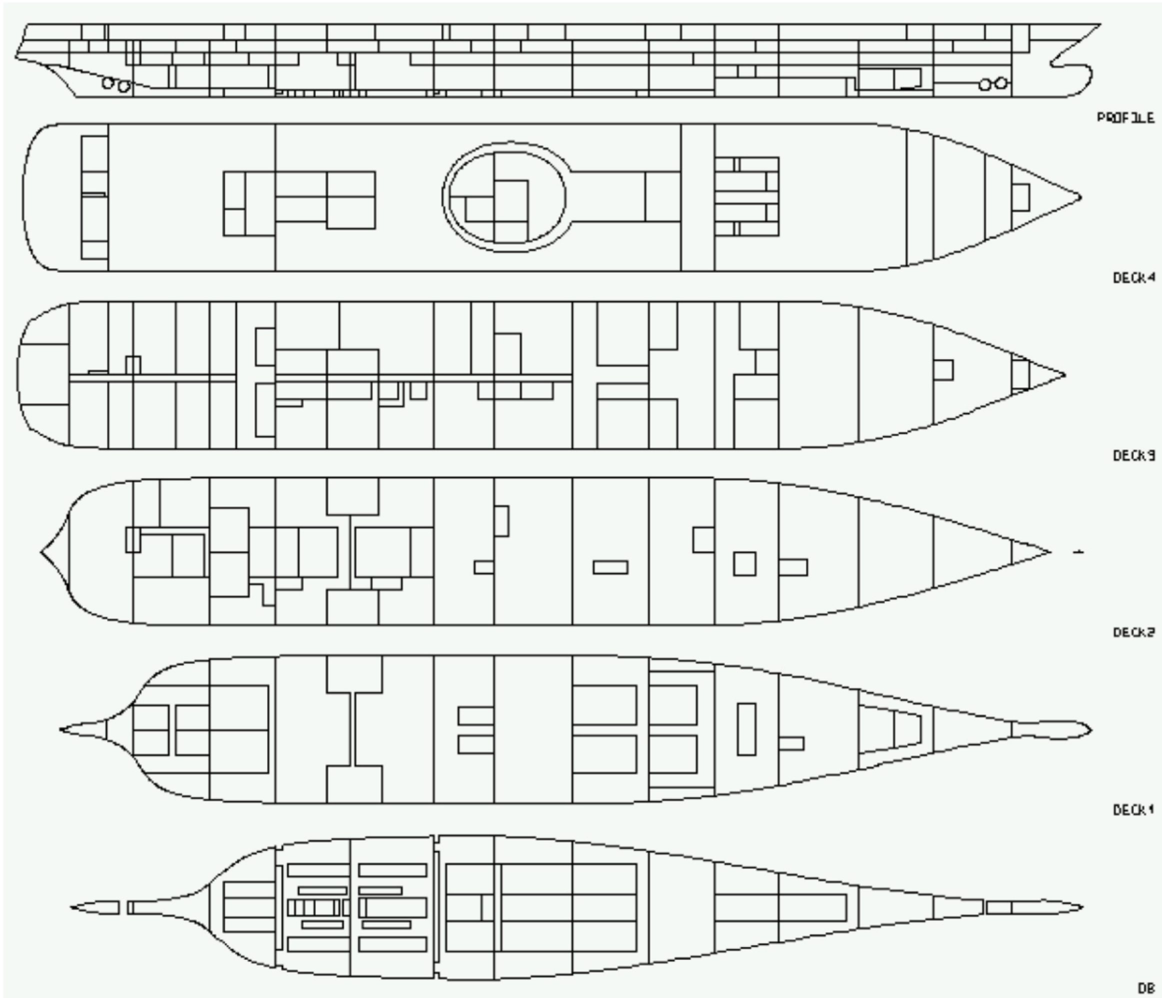

Fig. 2. Reference ship general arrangement (Luhmann, 2009).

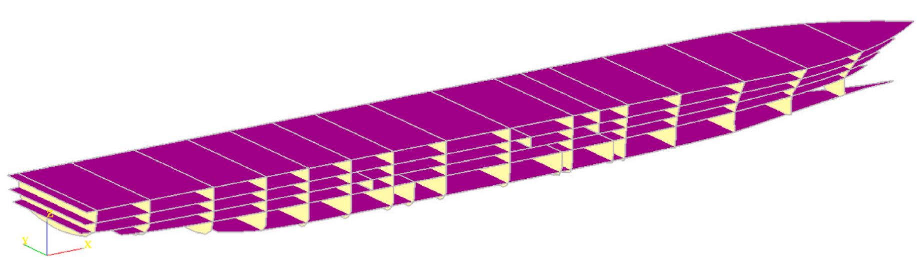

Fig. 3. SHARP super-element model of the reference ship.

4.1. Super-elements method

The super-elements method was introduced by Lützen (2001) and consists of dividing the ship into large independent structural units (the so-called super-elements), for which closed-form analytical formulations are available. These formulations are based on experimental and numerical data and characterise the resistance/energy dissipation of the super-element depending on its type and deformation mechanism. To simulate a collision, the vessel's dynamics should also be considered. More precisely, knowledge of the rigid-body motions due to external environmental loads and collision forces is needed. The present study uses the super-element software SHARP, where the rigid-body motions are implemented using a semi-coupled approach through the MCOL solver (Le Sourne et al., 2001), where the hydrodynamic characteristics of the ship are obtained from the Bureau Veritas seakeeping analysis code Hydrostar (BV, 2019).

By employing such assumptions and codes, software SHARP is capable of performing fast collision simulations with an acceptable level of accuracy, reconfirmed by a recent benchmarking study against FEM codes predictions (Kim et al., 2022). Fig. 3 shows a view of the super-element model employed for the calculation in SHARP.

4.2. Geometrical damage model

In the field of damage stability, there are multiple options to characterise and describe the geometry of collision damage. Such options depend on the assumptions of the calculation framework, especially during the design phase, or, in the case of a direct approach, on the kind

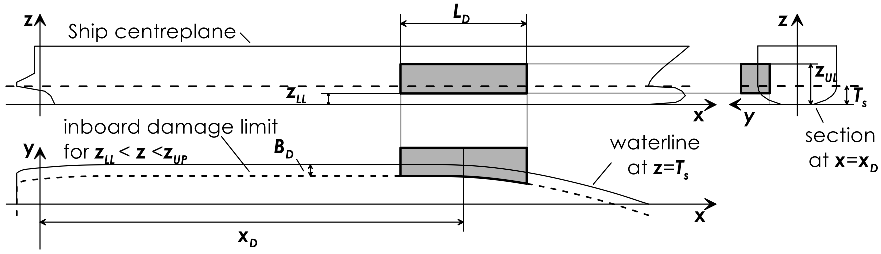

Fig. 4. Definition of collision damage according to SOLAS/eSAFE conventions.

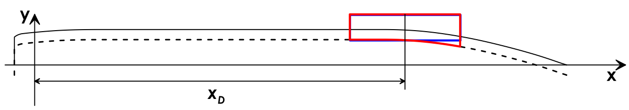

Fig. 5. Differences between box-shaped (*blue*) and SOLAS/eSAFE-shaped (*red*) damage.

of crash analysis employed for calculations. The standard collision damage defined by SOLAS (Safety of Life at Sea) and enhanced during the eSAFE project (Bulian et al., 2019) defines a somewhat unrealistic damage geometry, which follows the shape of the calculation waterline for the internal penetration limit. Such an approach is pursued during the design phase and applies mainly to static calculations for damage stability (Bulian et al., 2020). On the other hand, once dynamic calculations are carried out to simulate a flooding event, it is common practice to employ box-shaped damage geometry (Ruponen et al., 2019), leading to a different scenario compared to SOLAS damage (Mauro et al., 2023). However, in both cases, the breach's main dimensions and the location of damage are defined in the same way as follows.

- x_D: longitudinal position of the breach centre.
- L_D: damage length.
- B_D: damage penetration, measured inwards from the calculation waterline at x_D.
- z_{LL}: lower vertical limit of the damage (introduced during the eSAFE project).
- z_{UP}: upper vertical limit of the damage.
- I_{side}: identification of the damaged side (starboard or port).

Fig. 4 shows the geometrical definition of SOLAS/eSAFE-shaped damage, while Fig. 5 highlights the difference between SOLAS/eSAFE and box-shaped damages.

When direct crash analyses are carried out to simulate ship-to-ship collision, it is possible to determine the effective shape of the breach once FEM analyses are used. However, as this study is based on the employment of the super-elements method implemented in SHARP, such a detailed definition of the breach cannot be achieved. This is not a limitation, as the crash analyses should produce a damage characterisation easily readable by flooding analysis tools, which, most likely, employ a box-shaped damage definition. Then, the software SHARP can estimate the breach's main dimensions necessary to define box-shaped damages. More specifically, L_D, z_{LL} and z_{UP} are evaluated exactly as per SOLAS/eSAFE assumptions, and B_D is considered as the maximum penetration along the breach length.

Therefore, SHARP calculations can be employed to generate a database of collision damages to be used as a data source for the development of a surrogate model defining damage dimensions for survivability analysis after a flooding event.

5. Damage database generation

The damage model for a real-time risk assessment should be based on a database of direct calculations composed of outputs from crash analyses. As building a database requires the execution of a large number of simulations, the above-described method of super-elements implemented in the software SHARP is a viable solution to provide a damage characterisation easily useable for survivability calculations. In fact, it is necessary to perform a wide set of preliminary calculations in such a way as to obtain a global database, suitable to have a sufficiently accurate description of the potential damages that may occur in a specific operational area.

To define the database it is necessary to establish which are the potential striking ships (i.e., the targets) to be used in the crash simulations. Here, in the applied example, a set of 11 potential striking ships has been used, being representative of the worldwide fleet, as indicated by a dedicated study on crashworthiness (Conti and Hirdaris, 2020). Besides, the specific inputs of SHARP software should be considered, providing suitable inputs for the following set of data.

- Target ship initial surge velocity V_{strik}
- Ship initial surge velocity V_s
- Longitudinal impact position (i.e. the longitudinal position of the damage centre x_D)
- Collision angle α_c
- Target ship draught T_{strik}
- Ship draught T_{struk}

As a result, it is mandatory to follow a path aiming at saving computational time while granting a sufficient level of coverage for the damage-breach space. To this end, the design of experiments (DOE) is a suitable way to reduce the amount of observations needed to assess the variation of multiple dependent variables from independent ones.

5.1. Design of experiments

As mentioned above, DOE is a methodology that could help in reducing the number of calculations (i.e., experiments) necessary to adequately cover the design space. However, several methods could be pursued to achieve this goal. Of the many methodologies available for the generation of such experiments, the most commonly used are the factorial designs and their orthogonal variations (Box-Behnken designs, Central Composite designs, etc.). Such methods are used when surrogate models have to be derived from the experiment set. Factorial design space is an advantage when the interaction between different independent variables should be found. However, the method is intrinsically stratified, thus the independent variables assume only predefined values. Other options like random-based design are capable to cover the design space without stratification, but they do not grant an optimisation of the experiment in the execution like in factorial design.

In the present approach, a hybrid strategy has been followed considering the peculiarities of the independent variables to use and the physical necessities of the collision model employed for the direct crash

Table 3
Calculation draught for the reference cruise ship and the 11 striking ships.

ID	Ship type	T_{min} (m)	T_{inter} (m)	T_{max} (m)	D (m)	Δ_{max} (ton)
Ship	Passenger ship	6.50	7.20	7.80	9.80	63000
Target#1	Cargo Vessel	3.30	4.30	4.90	10.00	3500
Target#2	OSV	4.00	5.70	6.85	13.80	3500
Target#3	Chemical Carrier	5.50	6.80	7.60	10.60	11064
Target#4	Gas Carrier	5.50	6.40	6.92	17.95	16006
Target#5	Cargo Vessel	4.80	6.70	8.00	11.15	15415
Target#6	RoRo Vessel	5.50	6.30	6.80	15.80	22062
Target#7	Passenger ship	5.60	6.20	6.60	19.35	29558
Target#8	RoPax ship	5.90	6.50	6.90	15.32	30114
Target#9	Bulk Carrier	5.70	8.30	10.00	15.00	50000
Target#10	Container Vessel	8.00	10.70	12.50	24.60	119130
Target#11	Tanker	8.90	12.50	14.90	21.00	140000

calculations. According to the calculation assumption of software SHARP, the ship structure is considered symmetric concerning the longitudinal plane. Furthermore, early studies of database development performed with SHARP software were related to a collision in a fixed point x_D amidships, stratifying the other variables (Conti et al., 2022). However, the development of the collision database targets the whole ship length, which requires the adoption of a different strategy to select locations, as the presence of longitudinal bulkheads may affect the choice of specific locations or affect the distribution of results. It is then advisable to opt for a strategy capable of covering the design space. Studies performed with damage sampling procedures (Mauro and Vassalos, 2022) suggest the adoption of quasi-random (QR) sequences to equally fill a multidimensional space. Therefore, instead of stratifying all independent variables, the following hybrid space is proposed to generate collision scenarios in SHARP.

- Target ship type: stratified.
- Target ship initial surge velocity: stratified
- Ship initial surge velocity: constant equal to 0 m/s
- Longitudinal impact position: quasi-random
- Collision angle: quasi-random
- Target ship draught: stratified
- Ship draught: stratified

The V_S is set always to zero as used in previous studies on collisions employing SHARP (Conti et al., 2022) and in benchmark activities within the FLARE project (Kim et al., 2022). The number of calculations needed to build a sufficiently dense database is a function of the vessel and operational conditions. The present paper does not cover this specific topic that needs a dedicated study for further enhancement of the proposed methodology.

Applying the above-mentioned strategy for the reference ship, the following set of parameters has been selected to generate the hybrid space of the collision database.

- Target type: 11 ships.
- Target V_{strik}: stratified in [2,4,6,8,10] m/s.
- Ship V_S: constant 0 m/s.
- Longitudinal impact position x_D: 500 quasi-random samples in [$0.2L_{PP}$;$0.8L_{PP}$].
- Collision angle α_c: 500 quasi-random samples in [20; 90].
- Target ship draught T_{strik}: stratified in 3 draughts
- Ship draught T_{struk}: stratified in 3 draughts.

Table 3 presents the draught for the reference passenger ship and the 11 target ships. Additional information on the target ships may be found in Conti et al. (2022). The resulting design space is compliant with SHARP code limitations for x_D and α_c ranges and is composed of 500 scenarios per striking ship. The 500 scenarios are shown in Fig. 6 in a multidimensional representation of 5 variables. Fig. 7 shows the 500

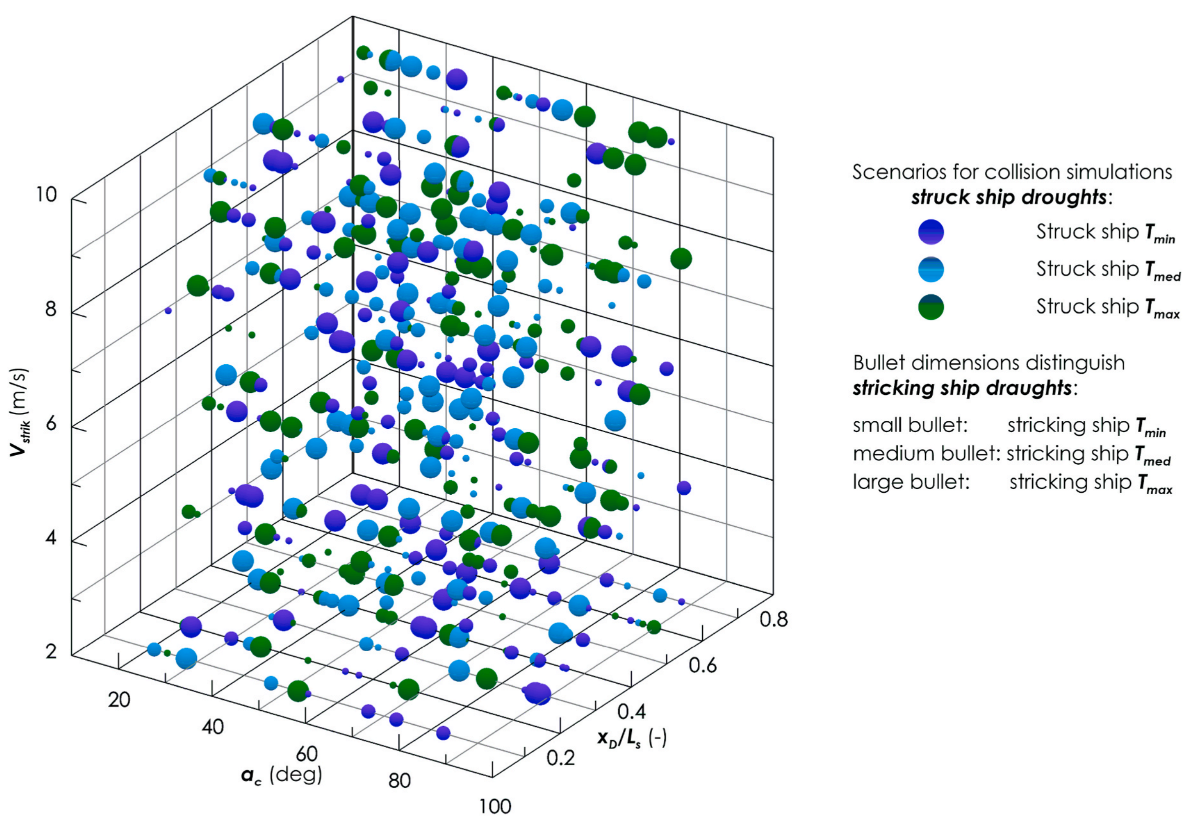

Fig. 6. Collision scenarios (500 cases) for each striking ship with hybrid DOE technique.

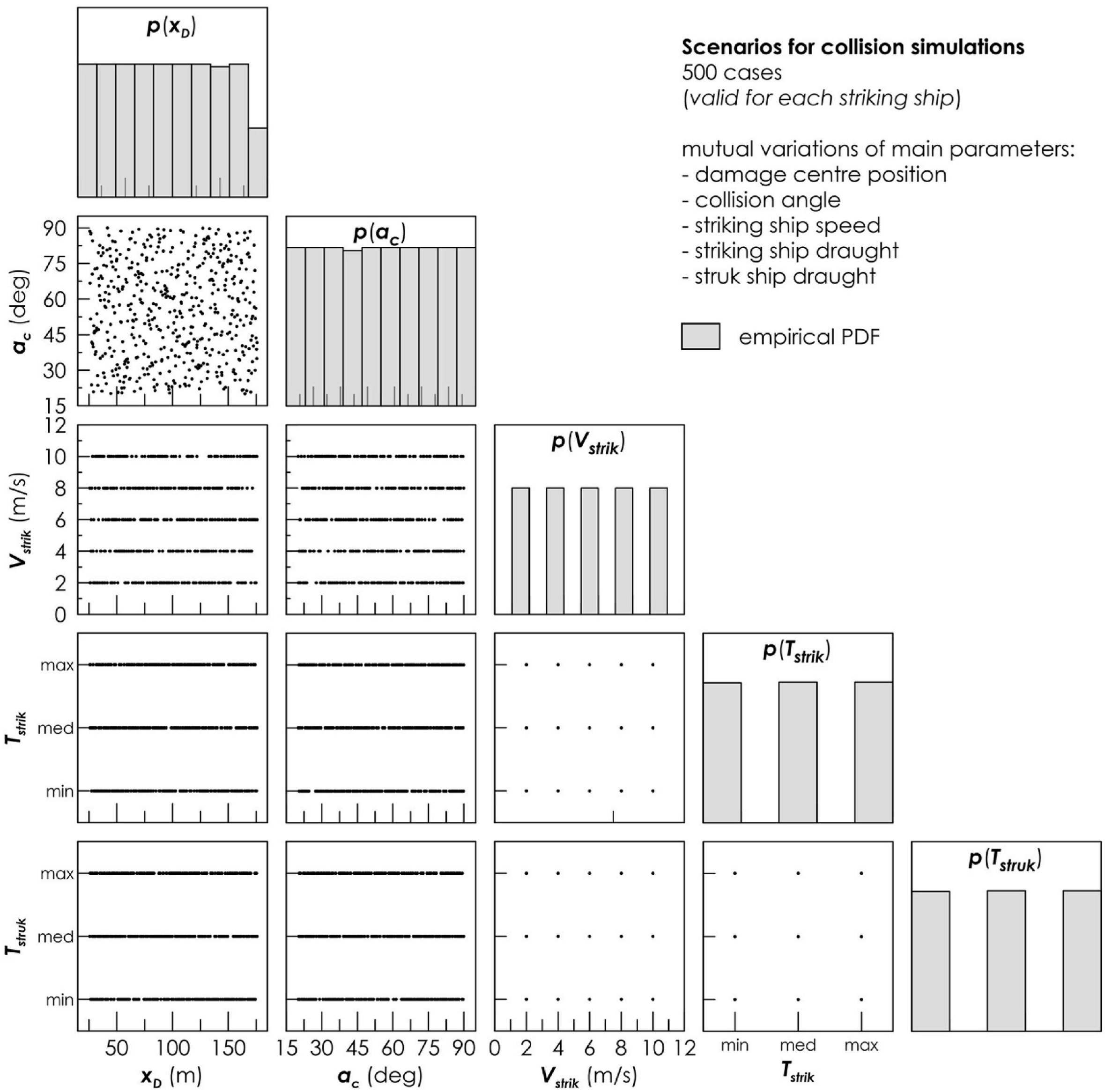

Fig. 7. Collision scenarios for each striking ship, parameters pairwise comparison.

collision scenarios, representing the pairwise comparison of the 5 independent variables.

Such scenarios are valid for the 11 target ships, leading to a total of 5500 scenarios to be simulated with SHARP. Fig. 7 explicates the nature of the sampling process showing the pairwise distributions of the sampled variables. The sampling process allows covering the x_D and α_c combinations with a uniform distribution thanks to the quasi-random sampling. Furthermore, the stratification in the other three dimensions of the design space allows for uniform coverage across the single substrata, with no unbalance between variables. The SHARP model of the reference ship is symmetric to the longitudinal plane; therefore, no distinction is necessary between the two sides of the ship, which means that variable I_{side} is not necessary for the given example. The definition of the database required approximately one week to run the 5500 scenarios on a laptop with an i7 2.4 GHz processor and 32 Go RAM.

5.2. Calculation results

The results exported from SHARP are limited to the geometrical characteristics of the damage, which means the length L_D, the penetration B_D and the vertical limits z_{LL} and z_{UL}. For the case of collisions, as mentioned earlier, the geometrical model of the damage is given by a box having two faces parallel to the waterline, two faces parallel to the transversal plane and two faces following the longitudinal shape of the calculation draught waterline.

Also within the provided code limitations, 295 scenarios end with computational errors, with a total of 5205 successful cases subdivided as follows: 486 for Target#01, 495 for Target#02, 491 for Target#03, 482 for Target#04, 478 for Target#05, 478 for Target#06, 410 for Target#07, 460 for Target#08, 493 for Target#09, 442 for Target#10 and 490 for Target#11.

It has been observed that some of the successful runs present damages for which the lower limit z_{LL} is above the reference drought of the struck ship. The results in Fig. 8 (showing the penetration and breach vertical limits as a function of damage location and longitudinal extension) highlight that there is sufficient coverage of the space of possible feasible damage geometrical parameters to study the generation of a surrogate model.

6. Surrogate models for breach dimensions

Software for real-time risk estimation on board passenger ships (or

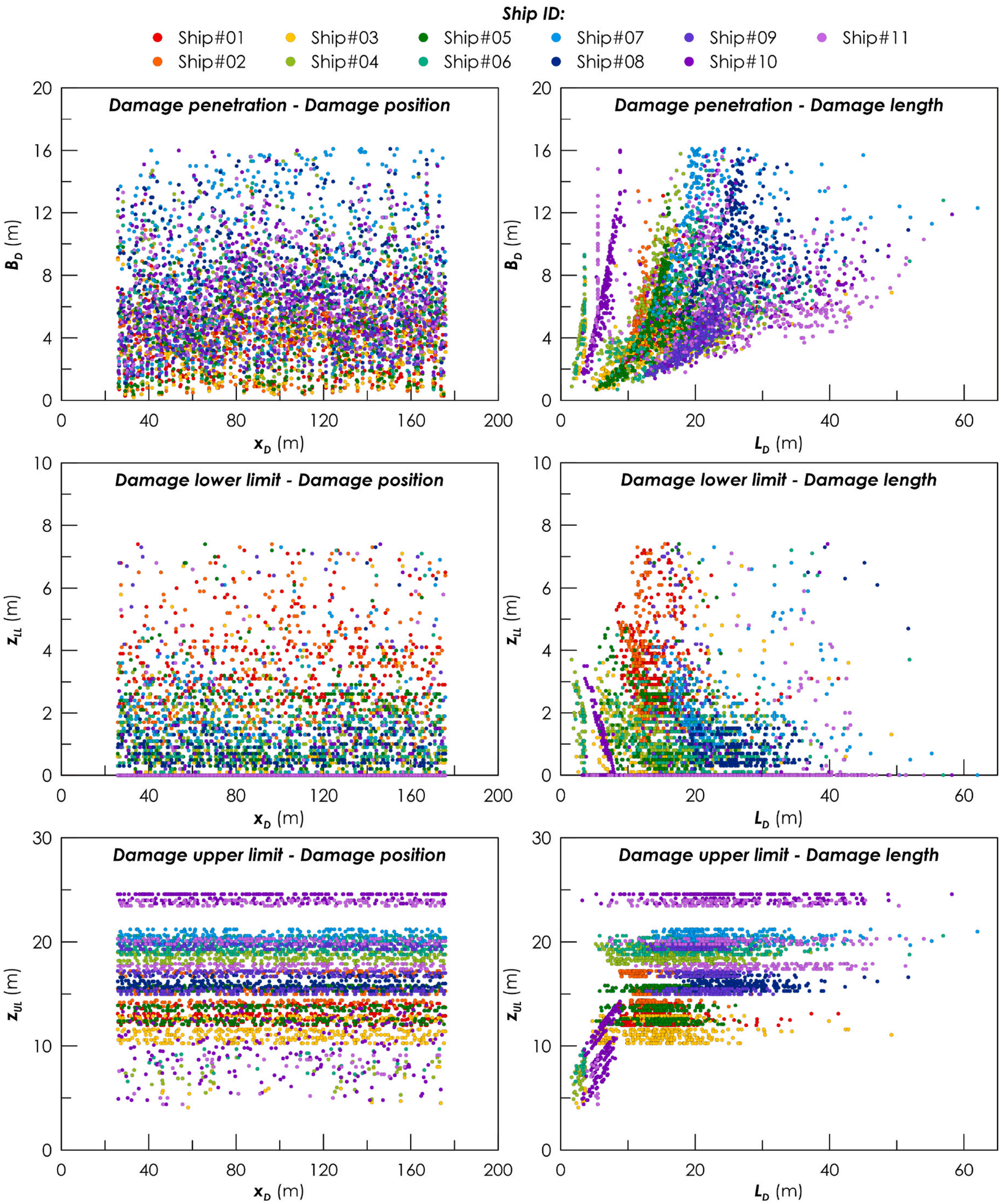

Fig. 8. Feasible breach dimensions from SHARP calculations on the 11 striking ships.

ships in general) should be capable of estimating the consequences of damage with specific dimensions and locations. Therefore, it is necessary to determine a model capable of providing a fast evaluation of the damage dimensions and locations derived from a set of input parameters. To this end, the adoption of surrogate models is particularly appropriate.

Surrogate models are simple analytical models that mimic the input/output behaviour of complex systems. Developing such models requires performing computationally expensive simulations at a set of carefully selected sample points. These models approximate the behaviour of the underlying complex simulations to a reasonable precision while also being computationally cheaper. Surrogate models can thus be seen as a simple representation of a complex system with potentially reduced accuracy in a given domain. The trade-off between the accuracy and the computational time is an important consideration during the construction of these models.

The construction of a surrogate model is comprised of three steps.

1. Selection of the sample points.
2. Optimisation or “training” of the model parameters.
3. Evaluation of the accuracy of the surrogate model.

Although several machine learning and regression techniques have been developed for surrogate model construction, there has been little

Table 4
Damage length surrogate model dimension and goodness of fit for the 11 ships.

ID	Multiple linear regressions		Neural networks		Forest tree	
	N. of coefficients	R^2	Layer sizes	R^2	Trained trees	R^2
Target#1	58	0.8082	[300]	0.6628	28	0.9975
Target#2	78	0.8797	[67]	0.8251	500	0.9992
Target#3	74	0.8161	[297 107]	0.7443	448	0.9992
Target#4	53	0.7880	[8288]	0.7338	496	0.9073
Target#5	67	0.9214	[276]	0.8747	87	0.9788
Target#6	57	0.7757	[34 2]	0.7251	100	0.8616
Target#7	46	0.9744	[268 54]	0.8998	465	0.9956
Target#8	84	0.9596	[55]	0.9215	487	0.9972
Target#9	63	0.8730	[8175 3]	0.9154	47	0.9508
Target#10	44	0.8267	[292]	0.8354	78	0.8766
Target#11	41	0.8647	[22 1]	0.7462	497	0.9426

Table 5
Damage penetration surrogate model dimension and goodness of fit for the 11 ships.

ID	Multiple linear regressions		Neural networks		Forest tree	
	N. of coefficients	R^2	Layer sizes	R^2	Trained trees	R^2
Target#1	47	0.7162	[17]	0.5655	250	0.9993
Target#2	67	0.6928	[9]	0.5172	495	0.9994
Target#3	50	0.8047	[12 2196]	0.7175	45	0.9507
Target#4	42	0.7475	[56 22 138]	0.7085	499	0.9965
Target#5	55	0.7866	[80 20 7]	0.7329	485	0.9981
Target#6	29	0.8250	[20 165 4]	0.7294	75	0.9256
Target#7	56	0.8170	[29]	0.7087	499	0.9645
Target#8	38	0.8596	[16]	0.7010	460	0.9998
Target#9	47	0.8638	[291 10]	0.8839	375	0.9914
Target#10	47	0.7450	[286 213 210]	0.7420	45	0.8178
Target#11	73	0.8650	[20 140 10]	0.8734	499	0.9197

work on how to best select the appropriate model for a particular application for either design space approximation or optimisation. For studies applying surrogate modelling techniques for process design and optimisation, models are mostly selected using process-specific expertise with no systematic basis for the selection.

For the stated problem of collision damages, surrogate models have to be built for the geometric characteristics of the damage. In this specific case, the selected variables are the damage length L_D, the damage penetration B_D, the damage lower limit z_{LL} and the damage height $H_D = z_{UP}$-z_{LL}. The damage height has been used because it was introduced to check the feasibility of the damage. The dependent variables of the model will be the same as those used for input in the DOE for damage generation.

In this explorative study, three different kinds of surrogate models have been tested, being representative of standard and advanced machine learning and regression techniques. More specifically.

- *Multiple linear regression*: adoption of a systematic method for removing terms from a generalised linear model based on their statistical significance in explaining the response variable. More specifically, a complete 4th-order polynomial has been used as a starting model (except for T_{strik} and T_{struk} with 2 as maximum order), removing the variables having a *p-value* associated with *F-statistic* greater than 0.1.
- *Neural networks*: for these models use has been made of the training algorithm available in MATLAB, optimising the network structure for the best reproduction of the initial data.
- *Forest tree*: for these models use has been made of the fitting algorithm available in MATLAB, optimising the tree structure for the best reproduction of the initial data.

Table 6
Damage vertical lower limit surrogate model dimension and goodness of fit for the 11 ships.

ID	Multiple linear regressions		Neural networks		Forest tree	
	N. of coefficients	R^2	Layer sizes	R^2	Trained trees	R^2
Target#1	59	0.7018	[11 20 11]	0.5297	204	0.8313
Target#2	44	0.7041	[6218 1]	0.4588	11	0.8082
Target#3	75	0.7870	[29 2]	0.7196	10	0.8289
Target#4	66	0.8630	[112]	0.8286	488	0.9931
Target#5	65	0.9001	[109 158 1]	0.8808	34	0.9728
Target#6	66	0.7632	[43]	0.6902	10	0.7680
Target#7	83	0.8451	[207]	0.7476	498	0.8961
Target#8	72	0.8620	[20]	0.7398	10	0.8203
Target#9	79	0.8240	[290]	0.7408	10	0.8540
Target#10	65	0.7150	[1 4 56]	0.5061	203	0.7389
Target#11	102	0.8066	[59]	0.6735	222	0.9600

Table 7
Damage height surrogate model dimension and goodness of fit for the 11 ships.

ID	Multiple linear regressions		Neural networks		Forest tree	
	N. of coefficients	R^2	Layer sizes	R^2	Trained trees	R^2
Target#1	59	0.6530	[56 204]	0.4267	27	0.7636
Target#2	56	0.7151	[135 43]	0.7355	499	0.9451
Target#3	80	0.5402	[51 6]	0.3244	10	0.7010
Target#4	70	0.3058	[284 1]	0.0546	10	0.6066
Target#5	65	0.8290	[7 1 47]	0.7980	343	0.9999
Target#6	19	0.1138	[73 2 2]	0.0322	92	0.0701
Target#7	83	0.8386	[19 23]	0.7907	498	0.9999
Target#8	72	0.8105	[229 297 176]	0.7153	72	0.8367
Target#9	79	0.9241	[58]	0.8510	38	0.9582
Target#10	58	0.4897	[5 5]	0.3092	10	0.5496
Target#11	51	0.3703	[81 8124]	0.2756	10	0.6853

The analysis of the goodness of fit of the three models has been checked using the mean squared error *MSE* and the coefficient of determination R^2, having the following forms:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - y_i^*\right)^2 \tag{7}$$

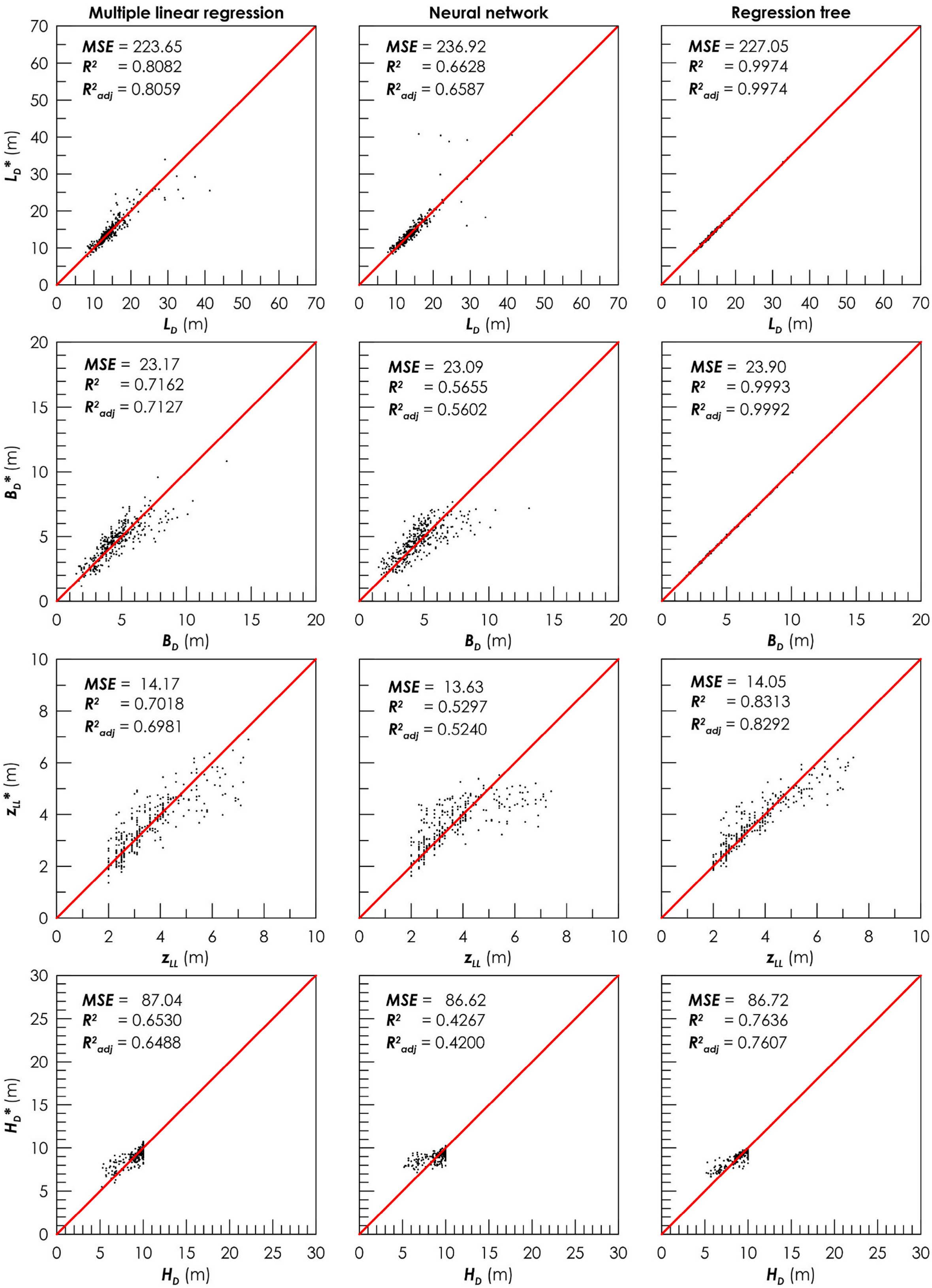

Fig. 9. Damage dimensions surrogate models, observed vs predicted for Ship#01.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - y_i^*\right)^2}{\sum_{i=1}^{n}\left(y_i - \overline{y}\right)^2} \tag{8}$$

where y_i are the observed values, y_i* are the predicted values, $\breve{y}$ is the mean of the observed values, and n is the number of observed values.

In the following sections, the main results of these three options are presented and compared, considering the adoption of ship-specific

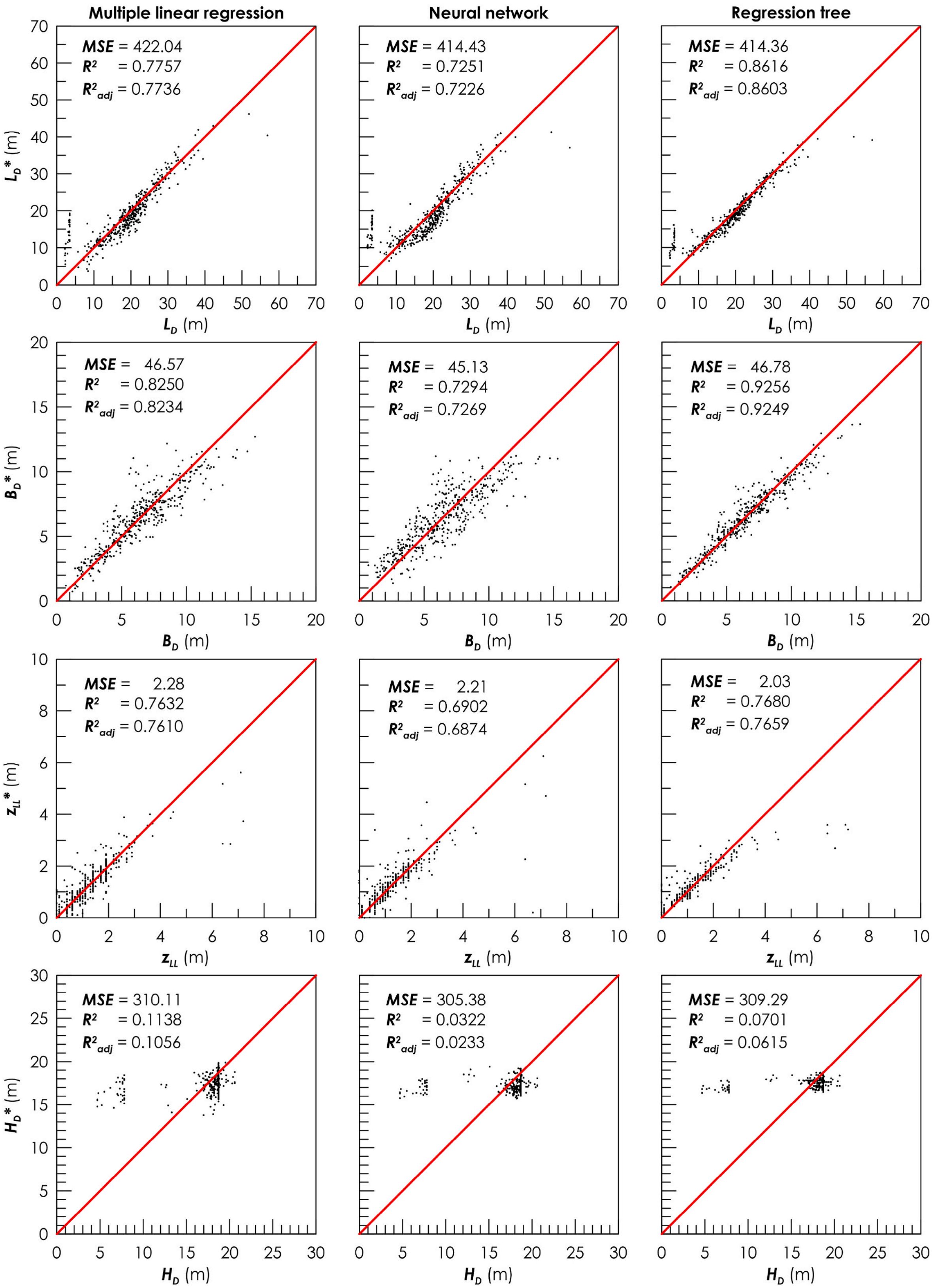

Fig. 10. Damage dimensions surrogate models, observed vs predicted for Ship#06.

models (one model for each striking ship), or a single model including all 11 striking ships.

6.1. *Ship-specific models*

As a first attempt to determine a surrogate model for ship dimensions, use has been made of the single subpopulation of damages

Table 8
Surrogate model dimension and goodness of fit considering all the 11 ships.

Variable	Multiple linear regressions		Neural networks		Forest tree	
	N. of coefficients	R^2	Layer sizes	R^2	Trained trees	R^2
L_D	175	0.8529	[7 15 1]	0.8487	99	0.9092
B_D	186	0.8498	[297 2]	0.8423	497	0.9324
z_{LL}	198	0.7700	[297]	0.7344	500	0.8966
H_D	173	0.6368	[83 155 294]	0.6606	351	0.7868

generated for each specific striking ship. For this specific case, the dependent and independent variables are the same as the construction of the database, therefore each of the damage characteristics L_D, B_D, z_{LL} and H_D is a function of x_D, V_{strik}, α_c, T_{strik} and T_{struk}.

The results of the regression and training analyses are reported in Tables 4–7 for the three analysed surrogate model types. The tables report the R^2 values for each quantity related to a specific striking ship. Besides, an indication of the complexity of the surrogate model is reported, giving the total number of regression coefficients for the multiple linear regression, the number and size of the layers of the optimum fit neural network, and the number of single trees used in the optimal forest tree. The table omits to report too specific quantities of training analyses for the conciseness of the paper, as they give no additional information to the aim of this explorative study.

What is observed from the results rpresented in the tables is the absence of a recognisable structure of the best-fit models through the 11 ships for all 4 damage dimensions. This is independent of the model used for the analyses. Considering the multiple linear regression model, the amount of regression coefficients is always changing, highlighting how the significance of a couple of terms between the dependent variables (i.e. the inputs for crash analyses) changes from ship to ship and also for different damage dimensions. Employing a neural network, the size and the number of layers identified for the best model are always different from each other, denoting a strong difference in the correlation between source inputs. It has to be underlined that probably the number of feasible solutions per striking ship is not large enough to have good results with neural networks. However, they have been considered also here for consistency of analysis through the paper. Also, the forest tree model reflects different architectures for the number of trees employed to fit the global forest model.

Observing the R^2 values, the general trend highlights that the best-fitting capabilities are given by the forest tree surrogate models. This is evident in the L_D, B_D and z_{LL} models for all the ships. The H_D quality of fit is also higher than other models except for particular cases, like Target#06. An overview of the model fit is given in Figs. 9 and 10, where the original and fitted results are reported for Target#1 and Target#6, respectively. In these figures, the red line represents the full correlation between fitted and original data, while the dots represent the effective relation between estimated and original data. The figures show also the *MSE* value for the given cases, which leads to the same considerations provided by R^2.

This behaviour of the surrogate models is probably related to the definition of the upper limit in the SHARP model, where damages are limited always to the maximum height of the struck or striking ship structural model (Conti and Hirdaris, 2020). Therefore, to improve the quality of the surrogate model it could be appropriate trying to identify a unique model to describe damage characteristics for all the ships. A last comment concerns the time needed to determine the surrogate models. The multiple linear regressions are fast to generate and need a few seconds to find the optimal structure of the regression. Different is the case for neural networks and tree forests, where a more complicated optimisation process is needed to define the optimal structure of the surrogate model. In such cases, the execution times require about 10 min per model on a regular laptop.

6.2. General models

Considering all the 11 striking ships for a unique surrogate model implies the adoption of additional dependent variables to describe the different vessels. Here, besides the dependent variables described in the previous sections (thus the input of SHARP simulations), ships are identified using three additional dependent variables describing the ship length L_s, the ship breadth B and the maximum draught $T_{\max}$, such quantities being available from AIS data. For the 11 ships, these data are listed in Table 3.

The same methods to generate surrogate models have been employed for this new subset of observations, introducing the newly mentioned parameters in the set of dependent variables. Results for the generated best models are provided in Table 8 with the same modalities given for previous case studies on ship-specific surrogate models. The results highlight that the general behaviour of these global surrogate models is better than the ship-specific cases concerning the average values of R^2. The multiple linear regression models show correlation coefficients above 0.6 for all the damage dimensions, with values above 0.84 for length and penetration. Neural networks have comparable performances with the previous simpler model. Therefore, it is probable that the number of observations used is still not large enough to benefit the regressions capability of the network. Forest tree has the highest R^2 for all the damage dimensions, providing satisfactory results also for H_D.

The comparison between observed and predicted damage dimensions is given in Fig. 11. Here, it can be observed that the dimension has more problems to be reproduced by all models in H_D. Once again, the reason should be searched in the modelling of damage provided as input to the fitting procedure. In any case, the regression and training using all the ships as input provide a significant improvement in the goodness of fit compared to the ship-specific models presented in the previous section.

The two different strategies to generate surrogate models, specific for striking ships or global, highlight that the global model gives more homogeneous results for the goodness of fit along the investigated four damage dimensions. Even though the R^2 value of some models specific for some ships is higher than the global one, the overall performances of global surrogate models give more confidence in the predicted values on the entire explored domain of collisions. This is true for all three methods tested, i.e., multiple linear regressions, neural networks and forest trees.

Comparing the methods for the global models, the best performance in terms of fit is granted by the forest trees, capable to have an R^2 above 0.9 for the damage length and penetration while having determination coefficient values above 0.78 for the vertical dimensions of damages. Such performances are not reached by the neural networks and multiple linear regressions. However, the latter and simpler methods provide R^2 values always above 0.60, providing the worst performances for the reproduction of H_D.

7. Real-time breach generation

After the determination of the surrogate models for damage dimensions it is necessary to test whether the proposed method is suitable for the real-time estimation of a breach generated by a potential collision. To this end, a fictitious accident has been hypothesised between the reference ship and a vessel having a length of 180.0 m, a breadth of 24.0 m and a draught of 4.0 m. The potential collision is supposed to occur at a location $x_D = 100$ m with a collision angle α_c of 65°, for three different target speeds, namely 2.0, 4.0 and 6.0 m/s, respectively. For the reference ship, the ship characteristics are those reported in Table 2, considering $V_s = 0.0$ m/s as for the assumptions of SHARP calculations.

The demonstration of the process should include the uncertainties of the hypothesised inputs. Therefore, uncertainties have been modelled

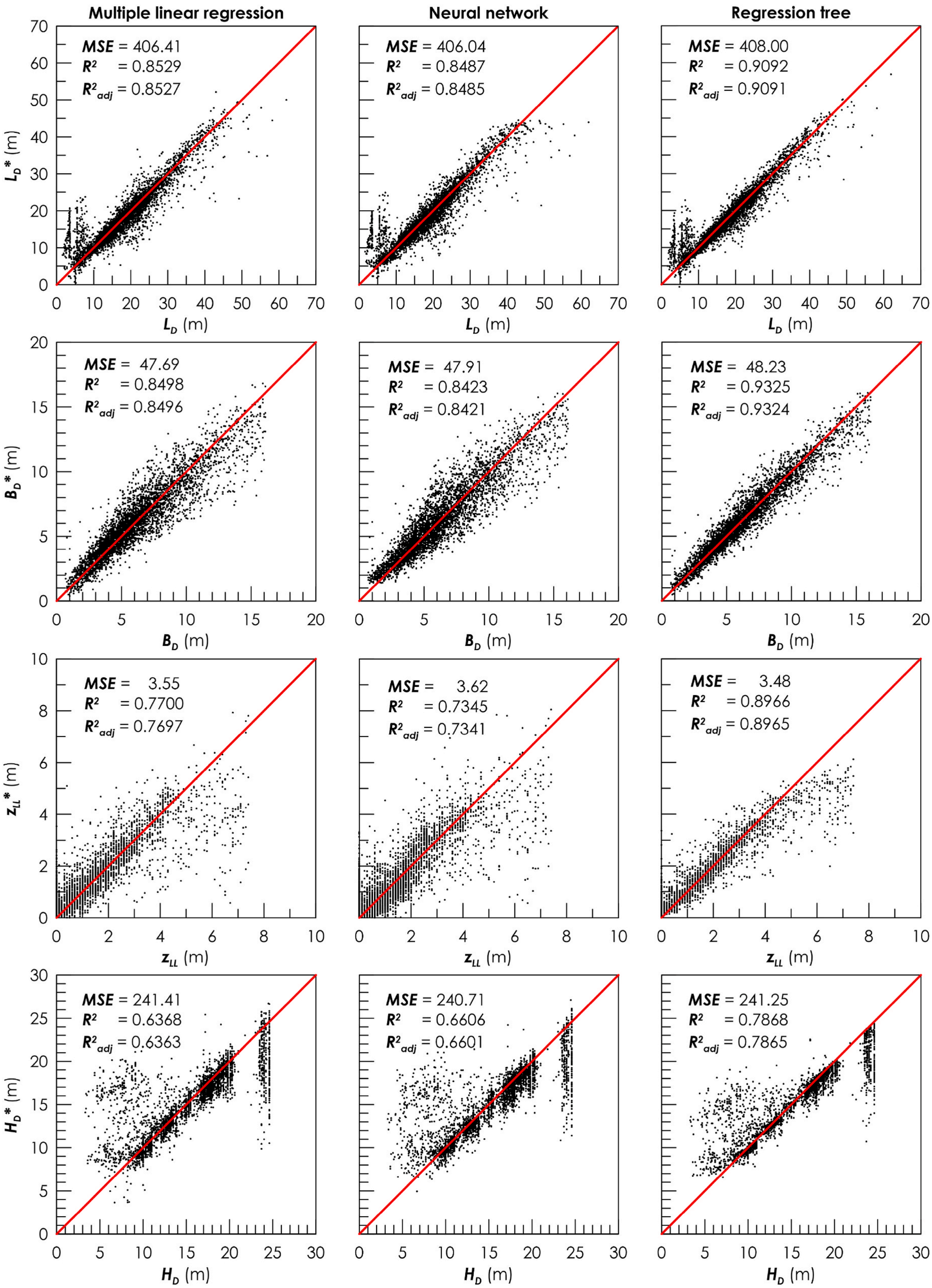

Fig. 11. Damage dimensions surrogate models, observed vs predicted for all ships.

according to equation (5) for striking ship speed V_T, the position of the breach centre x_D and the collision angle α_c. The standard deviation reference values have been set to 1.5 knots for the speed, 10 m for the breach position and 5° for the angle. These values are arbitrary and not intended to be proposed as the real value to be used on an onboard tool, they are just reference inputs used to test and demonstrate the applicability of the real-time breach generation. Because the process should be applied to the *PLL* calculation framework, the breach generation in

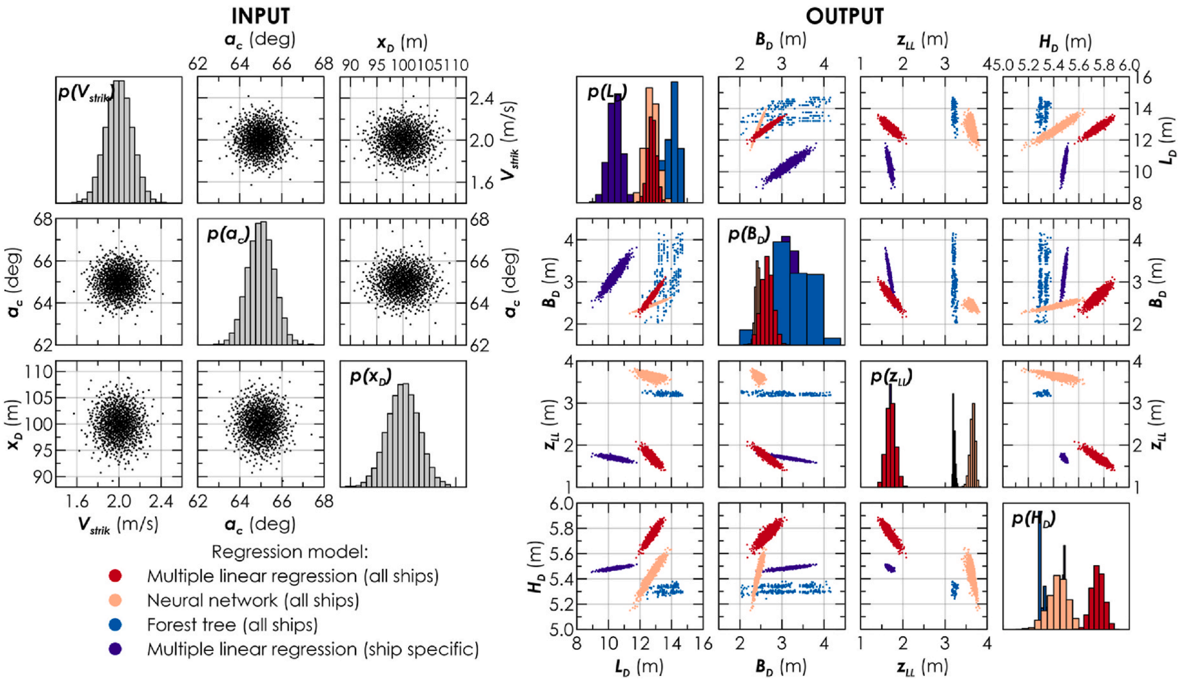

Fig. 12. Breach dimensions prediction according to different regression models for $V_{strik} = 2.0$ m/s.

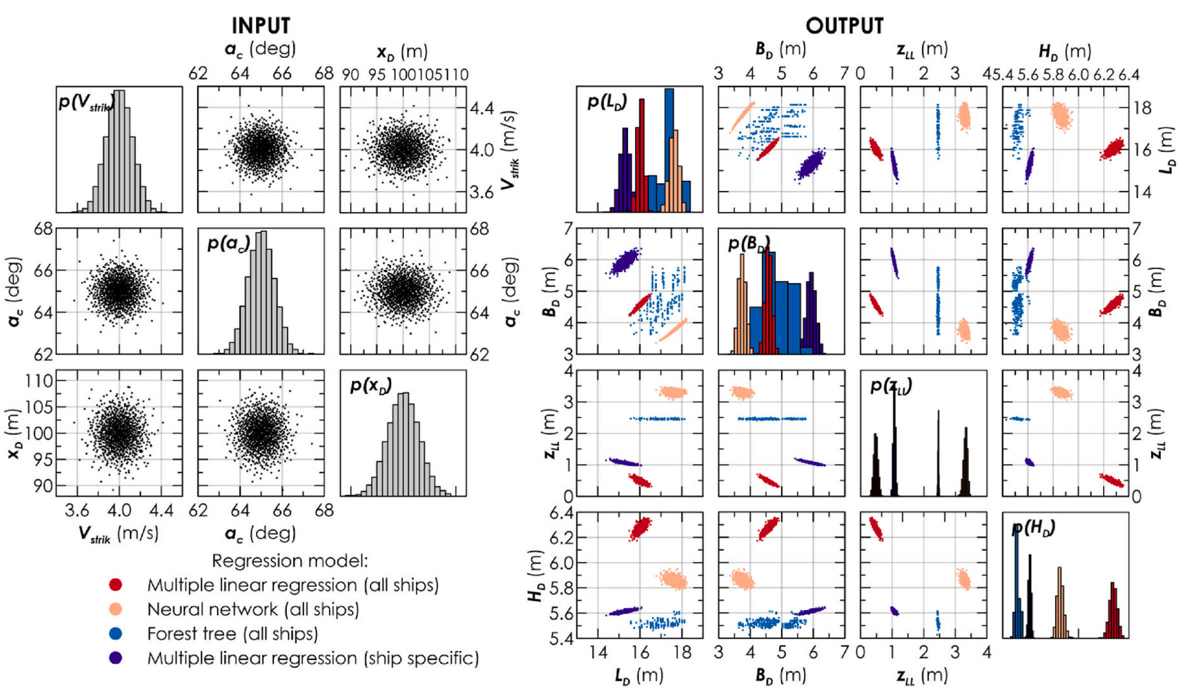

Fig. 13. Breach dimensions prediction according to different regression models for $V_{strik} = 4.0$ m/s.

real-time should produce a set of N_{QMC} breaches suitable to apply the Quasi-Monte Carlo integration of equation (6). Here, $N_{QMC} = 1000$ has been used for the verification of the calculation in real time.

Figs. 12–14 show the inputs and outputs of the damage surrogate model for the given example at the speeds of, 2.0, 4.0 and 6.0 m/s, respectively. The figures show the input and output distributions together with the pairwise comparison of the input and output variables. In the output, it is possible to observe the response given by four different regression models: multiple linear regressions on all 11 targets, neural network on all 11 targets, forest tree on all 11 targets and ship-specific multiple linear regression. The first three models are general and require the sole application of the surrogate model. For the ship-specific case, an additional step is needed to identify the ship which is closer to the identified target ship. Here, the specific ship is selected by evaluating the minimum Euclidean distance for length, breadth and draught concerning the identified target ship.

Analysing the figures, it is possible to observe that the four models provide different output values for the breach dimensions. This is the effect of the different R^2 values of the employed models. It is difficult to underline which of the regressions is going closer to reality as a reference real result is not present; however, it is assumed that the regression model with the higher R^2 is the one with the higher fidelity for the

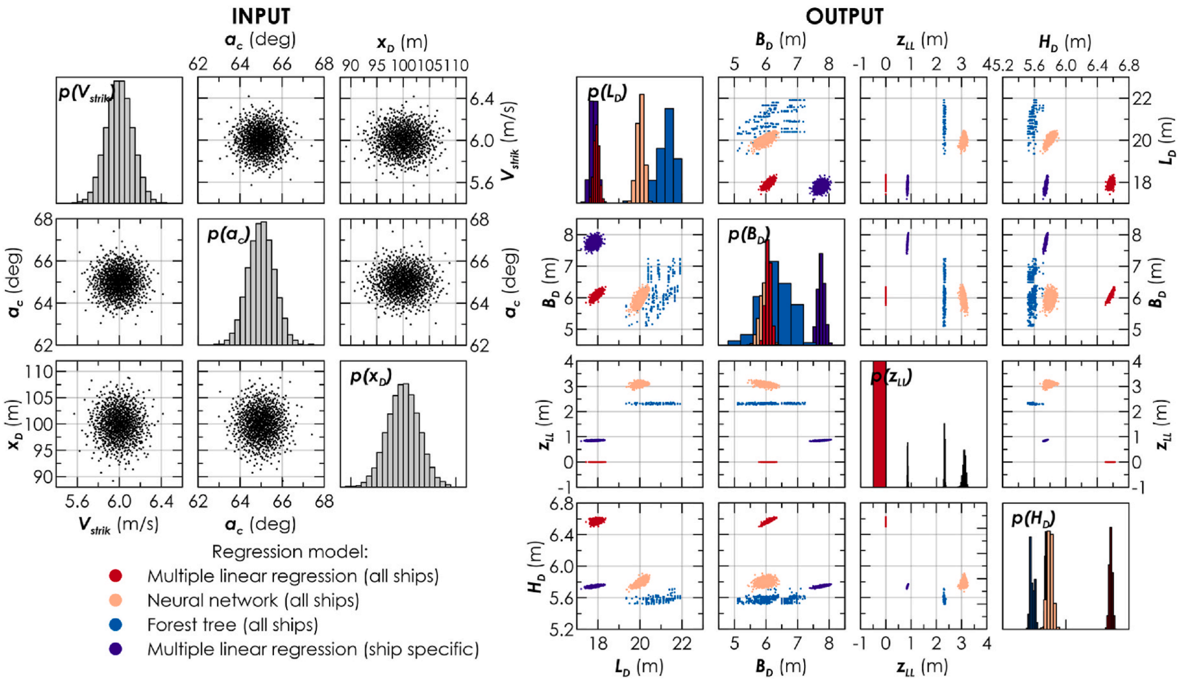

Fig. 14. Breach dimensions prediction according to different regression models for $V_{strik} = 6.0$ m/s.

obtained result. In this respect, the regression model employing the forest tree is the one with higher fidelity. It is interesting to observe the nature of the obtained output distribution in the case of the forest tree model. The resulting distributions are clustered because of the nature of the regression model. This is different from the results of neural networks and multiple linear regression, providing a more uniform coverage.

An important issue is the calculation time provided by the different models. Considering a single process on an Intel(R) Core(TM) i7-10750H CPU @ 2.60 GHz the multiple linear regression estimates the breach dimensions in 0.025 s both in the case of the general or ship-specific model, the neural network takes 0.044 s and the forest tree 1.2456 s. Therefore, even though forest three is providing the most reliable estimation of the breach it takes a longer time to estimate the damage dimensions. Only by running multiple processes in parallel (i.e., four processes), the calculation time is under 1 s, this being suitable for real-time estimation. It is then advisable to perform calculations with the multiple linear regression models, which are capable of running faster than real-time with higher reliability than neural networks for the case being considered.

8. Conclusions

In the present study, first-principles direct crash analysis is employed to generate a surrogate model of breaches to be used in a real-time onboard risk assessment for ship-to-ship collisions. The application of Super-Element methods available in the SHARP software allows for generating a large number of scenarios in a reasonable time, enabling the setting up of a suitable database of breach dimensions.

The present explorative study shows that with an initial population of about 4400 damages, the best fitting is given by forest trees. However, for simplicity of implementation in a real-time onboard risk assessment also a model based on multiple linear regression could be used. Of course, by increasing the number of the initial samples, the quality of the surrogate models may increase, not necessarily by increasing the samples of the DOE but more likely by increasing the number of striking ships to have more detailed coverage of the possible damage space.

Considering the uncertainties of the methods used to generate the damage dimensions from direct calculations, it is advisable to consider multiple linear regression models as a valid starting point for the early development of an onboard risk assessment tool. Once more detailed inputs are introduced into the database, the adoption of surrogate models derived from forest trees is advisable. Neural networks require the presence of a larger amount of data to be more effective than other presented models.

CRediT authorship contribution statement

Francesco Mauro: Conceptualization, Methodology, Calculations, Writing – original draft, Writing – Revised paper. **Fabien Conti:** Calculations, Writing – Revised paper. **Dracos Vassalos:** Supervision, Writing – Revised paper.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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