Damage stability of passenger ships: a multi-modal analysis for time to capsize

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ABSTRACT

After an accident in open seas, the final fate for a damaged ship could be the loss of stability and consequently capsize. The latter may occur even in calm water, but it is more critical and probable in adverse weather conditions, i.e., irregular waves. Identifying a possible capsize event and determining the time that it takes for the ship to capsize is extremely important for safety assessment, meaning whether it would be possible to evacuate the ship for the scenarios considered. In this respect, time domain simulations or model tests should be performed to provide answers to this question. However, in dealing with irregular waves, both approaches are affected by the random nature of the phase spectral components, which leads to a different time to capsize determination at each calculation/run or to the identification of cases where the vessel will not capsize in the analysed time window. Here, a dedicated study is presented to describe the Time to Capsize (TTC) in irregular waves for critical damages. Simulations performed on a real passenger ship, highlight the appearance of more than one capsize mode for the same damage case. A model based on Weibull and Mixed-Weibull distributions has been developed to describe the multi-modal behaviour of the TTC distributions for the analysed damage cases.

Keywords: *Damage stability, Time to capsize, Mixed-Weibull distributions, Extreme value theory, passenger ships.*

1. INTRODUCTION

The damage stability assessment for passenger ships (or ships in general) requires the investigation of the consequences of multiple hazards. Besides standard ship-to-ship collisions, which are included in the SOLAS framework (IMO, 2020), recent enhancements suggest considering also groundings and contacts in the flooding assessment (eSAFE, 2016, Bulian et al., 2020). Such an addition allows for a comprehensive overview of the potential hazards affecting the ship.

However, a thorough damage stability analyses should not be limited to the vulnerability assessment but should include an analysis of risk (Vassalos et al, 2022a, 2023). The damage stability framework developed in the FLARE (2023) project introduces the concept of flooding risk intending to consider first-principles analyses for the risk evaluation through the determination of the Potential loss of lives (PLL). The determination of risk is conceived in a multi-level mode, proposing different levels of approximations for the vulnerability and evacuation analyses (Vassalos et al., 2022b).

To this end, the role of direct flooding simulations is of utmost importance and should not be limited to survivability. A key requirement in the estimation of PLL relates to the evaluation of Time to Capsize (TTC), which could be estimated only through direct flooding simulations.

In the present work, a novel approach is proposed for the estimation of TTC through a detailed analysis of critical damage cases. It is noted that the diverse capsize modes that may occur in irregular waves for the same damage case leads to a multi-modal behaviour in the resulting TTC distribution. Therefore, a model based on Mixed-Weibull distributions is introduced to describe the TTC. This is possible by applying the extreme value theorem to the capsize problem, considering capsize as a system failure.

The application of Mixed-Weibull distributions to the TTC requires the determination of multiple parameters through a non-linear fitting, performed with a self-developed method based on an evolutionary algorithm (Mauro & Nabergoj, 2017).

Because an accurate description of TTC requires the execution of a large number of repetitions for each damage case, the proposed approach is suggested for the application to critical cases only. Here, an example is provided on a critical damage case for a large cruise ship employed for benchmark analyses in project FLARE (Ruponen et al., 2022b).

2. CAPSIZE OF A DAMAGED SHIP

The most dangerous fate for a ship, in general, and particularly for a passenger ship is a capsize or sinking event as a consequence of stability/buoyancy loss. As the capsize time is short compared to the conventional sinking process, it is extremely important to identify the conditions that may lead to a capsize event and potentially reduce or eliminate their occurrence.

Capsize modes

The identification of a capsize event and the evaluation of the time before this event after a hazard is of the utmost importance for the evacuation analysis of a vessel. In fact, in case damage could potentially lead to the sinking of the vessel, it should be possible to evacuate passengers and crew in less than half an hour. However, capsize may display a different nature depending on the interaction between floodwater and vessel motions and they are usually identified with the flooding state they relate to.

When the flooding process is studied, the following states can be identified after a collision:

- *Transient state*: is the first part of the flooding process. The water rapidly inrushes through the breach, causing a rapid and large heeling into or away from the breach side. The heeling process takes place in a time interval generally shorter than the vessel's natural roll period.
- *Progressive state*: in this stage, the water propagates through unprotected flooding paths within the ship, slowly diminishing stability until the vessel sinks, capsizes or reaches a stationary condition. This phase may take from minutes to hours.
- *Stationary state*: in this phase, there is no more significant water ingress/egress and the average ship motions are almost constant and a function of the external loads only.

An overview of the above-described flooding states is given in Figure 1. In case the capsize occurred during the transient phase, the consequences in terms of loss of lives are extreme, as the phenomenon is too fast to start the evacuation process. When an accident occurred in calm water, then the detection of a capsize is only governed by floodwater progression. In an irregular wave environment, the phenomenon is subject to the randomness of the sea state. In the latter case, it is then not possible to identify a-priori whether the capsize will occur or not in one of the three above-mentioned flooding states.

When a time domain simulation is performed, a capsize event can be easily recognised from the time history of the roll angle. Thus, when the roll signal exceeds a given threshold (generally above 40 degrees) the vessel is considered to have capsized. However, according to different damage stability frameworks, distinct capsize criteria can be found both for calm water and irregular seas:

- *Criterion 1*: SOLAS heeling failure that considers a maximum heeling of 15 degrees.
- *Criterion 2*: ITTC heeling failure that considers a maximum heeling of 30 degrees.
- *Criterion 3*: ITTC criterion on average heeling that considers an average heeling above 20 degrees in an interval of 3 minutes.
- *Criterion 4*: cases where the flooding process is not finished at the end of the simulation.

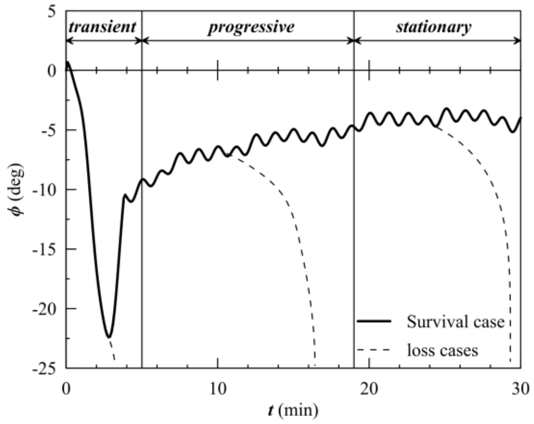

Figure 1: Stages of flooding for a damaged ship.

The first three criteria refer properly to the roll angle time history, whilst criterion 4 infers that the simulation time is not sufficient to cover the whole flooding process of the selected scenario. Thus, this last criterion is not properly a capsize criterion but could indicate a case where the ship loss may occur with a longer simulation time. In any case, all the above-mentioned criteria are not identifying a real capsize. However, they could be handy for the identification of critical cases for ship safety worthy of being analysed in more detail (Mauro et al. 2022a, 2022b).

Time to capsize

When a true capsize is detected, the identification of the TTC is straightforward for the case of calm water, as it is directly extracted from the roll time history of the single simulation:

$$TTC = t_{end} - t_0 \quad (1)$$

where t_{end} is the last time value of the simulation and t_0 is the time corresponding to the beginning of the flooding event. When simulations take place in irregular waves, the TTC is influenced by the randomness of the environment, leading to different TTC results for simulations performed with the same wave parameters. As a result, it is common practice to perform multiple repetitions of the same sea state and use the mean value of the case as a reference for the selected scenario (Cichowicz et al., 2016). In case Monte Carlo simulations are carried out to assess ship survivability, then a cumulative distribution of TTC is found for all the damage cases, considering just a few repetitions per each damage case in waves (Spanos & Papanikolaou, 2014).

However, a reliable evaluation of the possible risk of loss of lives requires the knowledge of TTC for those critical cases that are worthy to be investigated with evacuation analyses (Vassalos, 2022, Vassalos et al., 2023). Therefore, a more accurate and appropriate procedure for TTC determination should be investigated to be applied only to a restricted number of critical cases.

The conventional approaches to TTC do not consider in detail the nature of the capsizes detected during the time-domain simulations. Furthermore, the relatively (or excessively) small simulation time does not allow for recognising properly reliable distributions for the TTC, legitimising the assumption of taking the mean value among the repetitions as significant TTC for further analyses. However, the numerical time-domain simulation codes benchmarking activities within the FLARE project (Ruponen et al. 2022a, 2022b) allow for analysing more in depth single damage case scenarios, comparing 20 repetitions for a single damage scenario. The results obtained with the PROTEUS3 solver for a cruise ship are reported in Figure 2, highlighting the different nature of the capsize within 20 repetitions in irregular waves.

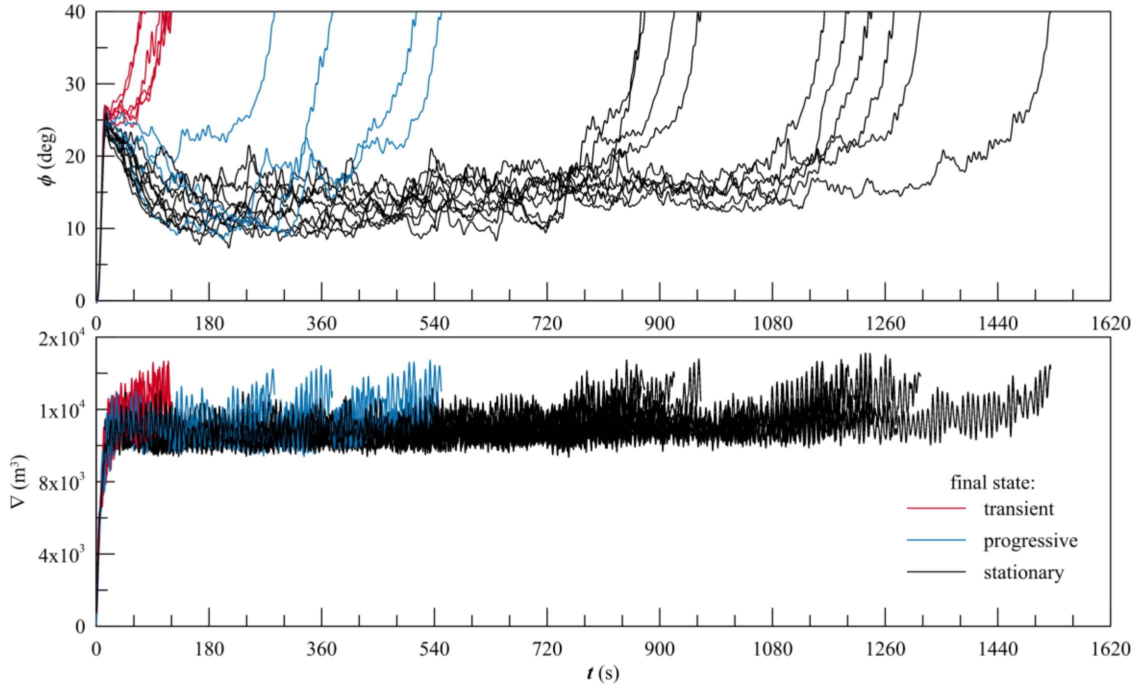

Figure 2: Roll angle (top) and floodwater volume (bottom) time traces for 20 repetitions of the same sea state and damage for the FLARE benchmark cruise ship employing the PROTEUS3 solver.

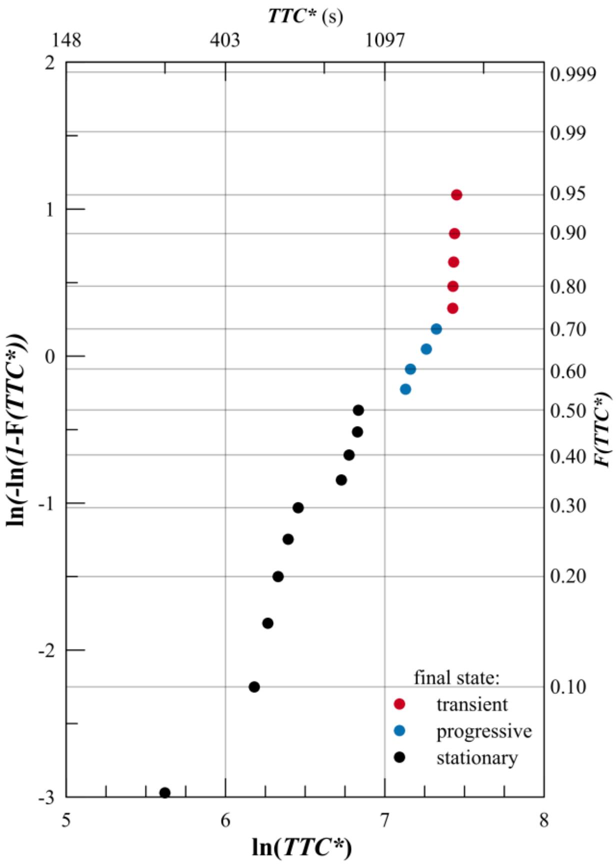

Figure 3: TTC* values representation on the Weibull plot for the FLARE benchmark cruise ship case study.

From Figure 2, it is possible to recognise the three different capsize modes described in the previous section. All 20 repetitions end with a capsize; more precisely, 6 are transient, 4 progressive and the remaining 10 are forced oscillations capsize whilst in what was described earlier as stationary state (stationary state capsize mode). The time trace of the roll angle is not helpful to distinguish between progressive and stationary state capsize modes; however, from a direct time-domain simulation (e.g., performed by PROTEUS 3 software) it is also possible to monitor the amount of floodwater entering/leaving the ship during the flooding process. Therefore, by analysing the water volume (the bottom graph in Figure 2) a distinction can be made between progressive and stationary-state capsize modes.

The simulations show a net distinction between the three different capsize modes, highlighting a grouping of the simulations having similar TTC. Therefore, it is reasonable to assume that the three different capsize modes follow independent distributions instead of a single one. Such an observation requires a more detailed analysis of the TTC estimation, with particular emphasis on finding suitable probabilistic distributions that may be used to describe the various phenomena.

3. MODELLING CAPSIZE AS A SYSTEM FAILURE

Determining suitable distributions to model the TTC is a somewhat new topic in damage stability. It is common practice to assume that TTC is associated with a random Gaussian process and consider the mean of multiple repetitions as a significant value for the analyses.

To enhance the perception of TTC, it could be useful to interpret the capsize as a failure of a system (i.e., the damaged ship). In such a way, it is possible to associate the failure with the commonly used distributions for failure analyses as e.g., Weibull distributions. However, to properly analyse the TTC as a failure it is handy to define an auxiliary time to capsize TTC* defined as follows:

$$TTC^* = t_{\max} - TTC \qquad (2)$$

where t_{max} is the maximum allowed simulation time for the damage stability flooding analyses (usually set to 30 minutes). Then, it is possible to adopt for TTC* the common representations for failure cases on the Weibull plot, as shown in Figure 3. On the Weibull plot, a distribution following a 2-parameter Weibull model follows a straight line whilst 3-parameter distributions present only a concavity or convexity. In the given example of Figure 3, it is possible to observe that the different capsize modes are not following a single distribution. Therefore, a more detailed analysis is needed to identify a suitable distribution for the TTC*.

Failure distributions

According to the change of variable identified by equation (2), the minimum values of TTC, corresponding to the transient capsize cases, become the maxima of the TTC*. Therefore, with transient capsize cases being the most critical to assess vessel survivability or PLL, it is extremely important to capture such phenomena, thus reproducing with sufficient accuracy the tale of the TTC* population. To this end, the extreme value theorem could aid in identifying a suitable distribution for the TTC* description.

As for the multiple repetitions of flooding simulations, all capsizes are considered, and the lower limit to define the capsize event is given by the

Fisher-Tippet-Gnedenko theorem (Berliant et al., 1996), stating that the Generalised Extreme Value Distribution (GED) should be used to describe the phenomenon under analysis.

GED can be described by the following cumulative density function:

$$F(x) = e^{-t(x)} \tag{3}$$

where:

$$t(x) = \begin{cases} (1-\beta z)^{-1/\beta} & \text{if } \beta \neq 0 \\ e^{-z} & \text{if } \beta = 0 \end{cases} \tag{4}$$

and:

$$z = \frac{x-\gamma}{\eta} \tag{5}$$

The three real constants in equations (4) and (5) are the shape parameter β, defined in (0,+∞), the scale parameter η, defined in (0,+∞), and the scale parameter γ, defined in (-∞,+∞), The shape parameter value identifies three particular sub-cases of the GPD: the Weibull, the Gumbel and the Frechet distributions, respectively. The Gumbel distribution, obtained for β=0, defines the extremes of populations, which are supposed to follow an exponential distribution. Freshet distribution (β>0) is used for particular populations having a significant amount of data at the tale end (the so-called fat-tale distributions), through a change of sign in the x values. Finally, the Weibull distribution (β>0) represents all the cases not covered by the previous two distributions and is widely used for engineering problems related to defect data analyses.

Here, Weibull distribution is used as the basis for TTC* analyses. Therefore, it is convenient to rewrite equation (5) in the standard form adopted for three-parameters Weibull distribution:

$$F(x) = 1 - e^{-\left(x-\gamma/\eta\right)^{\beta}} \tag{6}$$

Equation (6) is defined for location parameter values such as x> γ. However, for particularly complicated cases subject to high levels of non-linearities (Mauro & Nabergoj, 2016) the use of a simple 3-parameters Weibull distribution is not enough to represent the data. This is the typical case of multi-modal responses, i.e., sample data that could present more than one population. A good representation could be obtained by employing the so-called Mixed-Weibull distribution in such cases. Such distribution is a combination of two or 3-parameters Weibull distributions, resulting in the following cumulative density function:

$$F(x) = 1 - \sum_{i=1}^{N_D} w_i e^{-\left(x-\gamma_i/\eta_i\right)^{\beta_i}} \tag{7}$$

where N_D is the number of subpopulations and w_i are the percentiles of subpopulations in the total population such that $\sum w_i = 1$. The other parameters are the same as for the three parameters Weibull defined in equation (6). There are no limitations on N_D but as N_D increases the number of parameters to estimate increases too. For example, fitting a 2-subpopulation Mixed Weibull distribution requires the estimation of 7 parameters, 3 subpopulations require 12 parameters and so on.

For such a reason, it is necessary to identify a proper method for the estimation of a high number of parameters.

Parameter determination

Different methods can be adopted to estimate the parameters of standard 2-parameter Weibull distribution, like the least-square fitting, the method of moments, the maximum likelihood and so on. All these methods can be extended to the case of a 3-parameter Weibull distribution. Due to the high number of unknowns in the case of a Mixed-Weibull, the aforementioned methods cannot be directly used, and sometimes manual fitting of data is common practice. To set up an automatic process for the parameter estimation, a differential evolution algorithm has been used, which provides an enhanced and extended version of the least square fitting method. The process has been already compared with conventional fitting methods in the case of 2 and 3-parameter Weibull distributions (Mauro & Nabergoj, 2017), highlighting the reliability of the process in case of need for a higher number of unknown parameters. For this reason, the differential evolution approach is here used for the estimation of the unknowns in the fitting of Mixed-Weibull distributions.

4. APPLICATION ON A PASSENGER SHIP

The developed analyses described in the previous sections are applied here on a reference case employed throughout several studies in the FLARE project. The test case refers to a large passenger ship (more precisely a cruise vessel) having the general arrangement shown in Figure 4

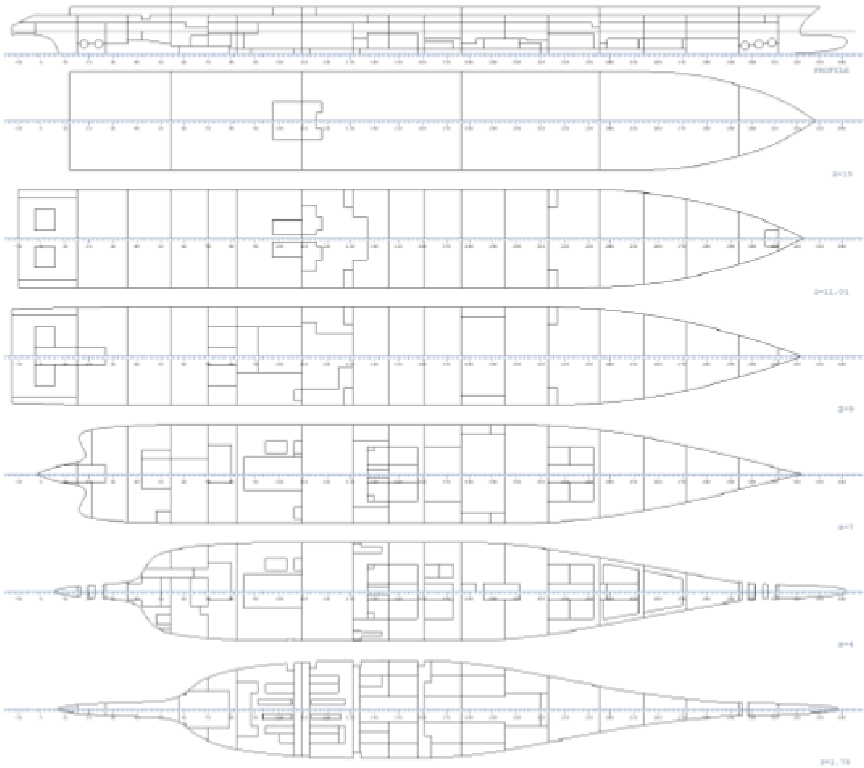

Figure 4: general arrangement of the reference passenger ship.

Figure 5: longitudinal view of the reference damage breach.

Table 1: main characteristics of the reference passenger ship.

Parameter	Value	Unit3
Length overall	300.0	m
Length between perpendiculars	270.0	m
Beam	35.2	m
Subdivision draught	8.2	m
Height at main deck	11.0	m
Metacentric height	3.5	m
Deadweight	8,500	T
Gross tonnage	95,900	T
Number of passengers	2,750	-
Number of crew members	1,000	-

and the main characteristics given in Table 1. The vessel is the same employed for the benchmark studies (Ruponen et al., 2022b) and advanced investigations on first-principles-based damage stability frameworks (Mauro et al., 2022a, 2022b).

Reference damage case

To apply the TTC analyses, a reference damage case has been selected, being the same as the benchmark tests, thus the one shown in Figures 2 and 3 for the time traces and the Weibull plot, respectively. However, the model employed for the benchmark studies refers to a simplified internal layout of the vessel. Here, to address a more realistic case, the full compartmentation of the vessel is used, as it is represented in Figure 4. Such an internal subdivision follows the guidelines for time-domain flooding simulations established and consolidated within the project FLARE (Guarin et al. 2021).

The selected breach damage has a length of 44.2 m, a penetration of 10.0 m a height of 16.0 m starting from a lower vertical limit of 0.0 m.

Figure 5 provides an overview of the breach location and dimension in the longitudinal view of the reference ship. The damage is representative of a significantly large and critical damage for the reference ship, resulting from a preliminary set of calculations. This preliminary set of calculations represents a stress test for the ship, including only damages with the maximum allowable damage length by SOLAS and severe sea states with significant wave height H_S=7.0 metres (Vassalos & Paterson, 2021).

Here, with the 7.0 metres wave height being not realistic as an operational scenario and also outside the reliability bounds of the flooding simulation code, two alternative weather conditions have been considered with H_s=3.75 and H_s=4.25 m.

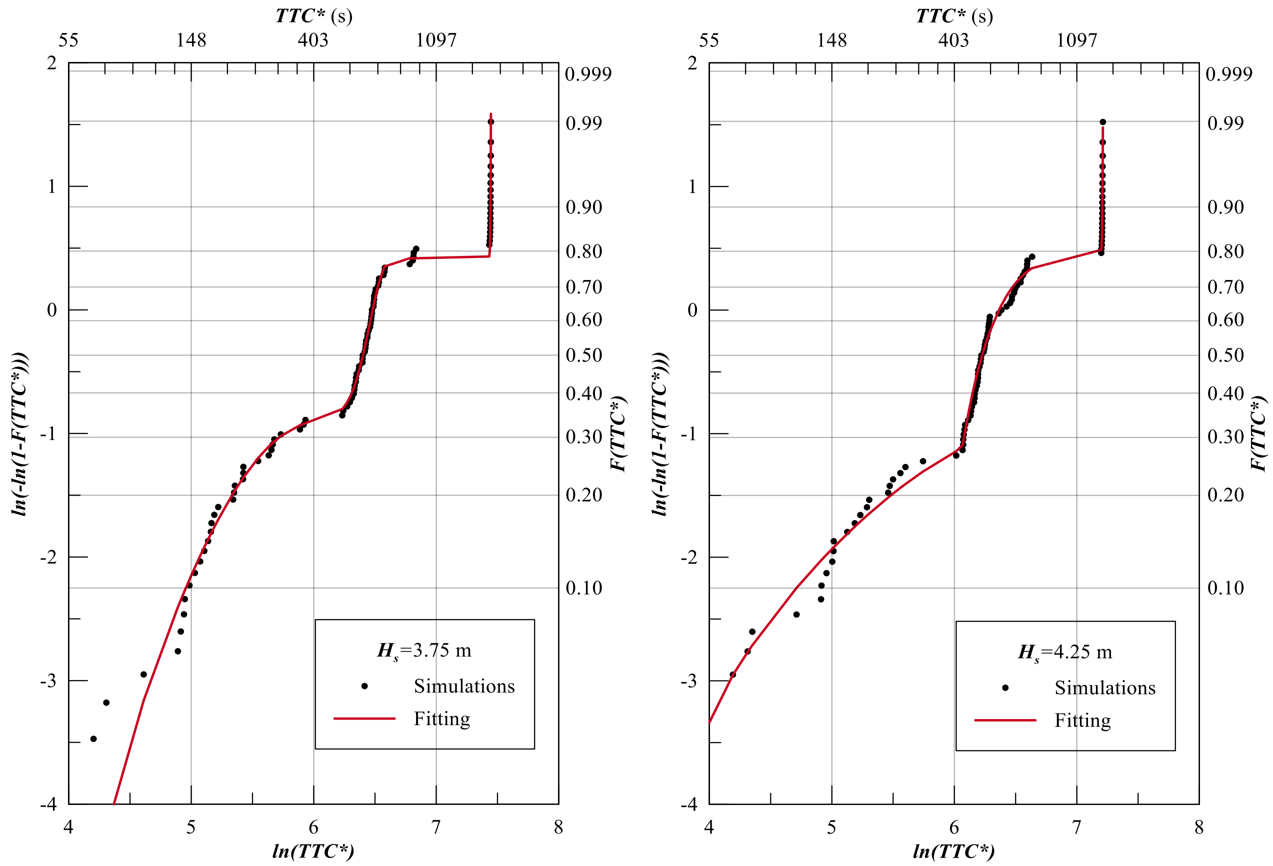

Figure 6: TTC* values and Mixed Weibull fitting on the Weibull plot for the reference damage case with H_s=3.75 m (left) and H_s=4.25 m (right).

Table 2: best-fitting parameters for the Mixed-Weibull distribution on the reference damage case.

	Parameter	Distr. 1	Distr. 2	Distr. 3
H_s=3.75m	η	178.917	310.997	931.324
	β	1.895	5.179	208.190
	γ	39.774	336.768	776.948
	w	0.341	0.273	0.386
	R^2	0.998		
	R^2_{adj}	0.997		
H_s=4.25m	η	253.183	120.584	630.453
	β	0.985	1.099	137.552
	γ	27.707	429.318	721.063
	w	0.346	0.265	0.389
	R^2	0.996		
	R^2_{adj}	0.995		

For both environments, 100 repetitions have been carried out to take into account the random nature of the irregular waves. This number of simulations has been selected in order to perform more than the 20 simulations used for the benchmark analyses so as to have a sufficient number of points necessary to identify the possible distributions describing the different natures of the capsize event

TTC analyses

The reference damage case consists of simulations having a maximum time of 30 minutes, as suggested by past and recent studies on damage stability (Spanos & Papanikolaou, 2014, Guarin et al.,2021, Mauro et al. 2023). All the simulations, both for 3.75 and 4.25 metres of significant wave height, led to the vessel capsizing within 30 minutes. Therefore, the resulting set of 100 capsizes per wave height represents a suitable population for the fitting methodology described in the previous section.

Figure 6 presents the Weibull plane for the distributions of TTC* resulting from simulations together with the fitting curve obtained by the application of the differential evolution algorithm. Even though the fitting seems to capture the population's behaviour well, it was thought appropriate to check the goodness of fit through conventional estimators. In this case, use has been made of the R^2 and R^2_{adj} coefficients, defined as follows:

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

$$R^2_{adj} = 1 - \left(1 - R^2\right)\frac{n-1}{n - n_p - 1} \tag{9}$$

where y_i are the n observations, y_i^* the predicted values, $\bar{y}$ is the mean value of the observations and

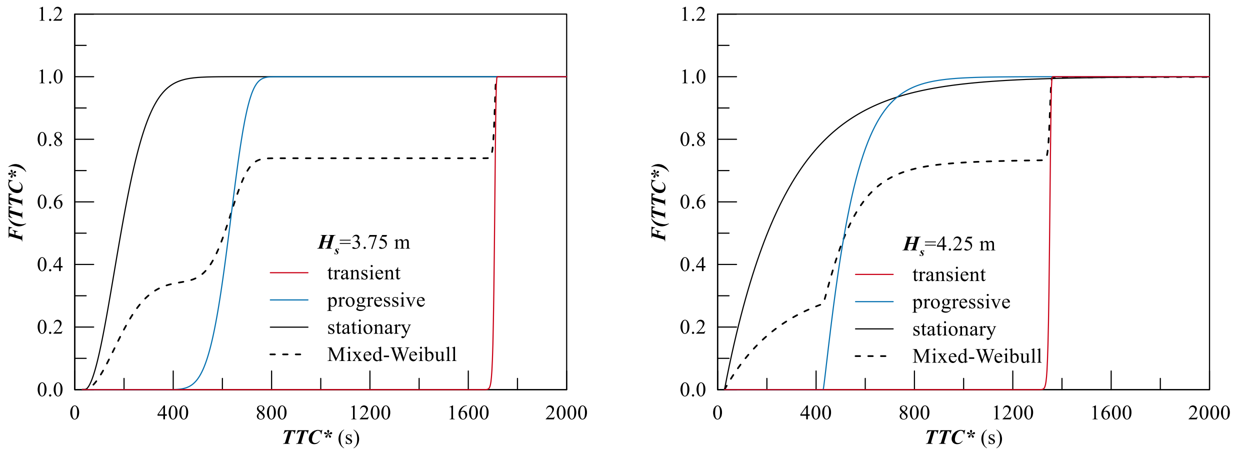

Figure 7: cumulative density functions for the transient, progressive and stationary capsize for the reference damage case considering H_s=3.75 m (left) and H_s=4.25 m (right).

n_p is the number of parameters used in the regression model.

Employing the above indicators makes it possible to evaluate the quality of the proposed regression model. Table 2 gives the obtained regression parameters and the goodness of fit indicators, where it is possible to observe the quality of the regression.

For both analysed cases, the R^2 and R^2_{adj} values are above 0.99, highlighting the good quality of the obtained regression models. The values shown in the table allow for a more accurate description of the distributions that characterise the different capsize modes. The location parameter γ allows for identifying the capsize type. High values of γ refer to the transient capsize as high TTC* corresponds to a low TTC value according to equation (5). Therefore, Distr.3 in Table 2 models the transient case. Adopting the same considerations, Distr.2 is for tor the progressive capsize case and Distr.1 is for the stationary case. The scale parameter η does not add additional considerations for the characterisation of the capsize event. On the other hand, the shape parameter β identifies how the capsizes are distributed along TTC*.

The transient capsizes (Distr.3) present a high β value, which means that they are all distributed along a short TTC* interval. The progressive and stationary capsize present a different shape compared to the transient as they cover a wider interval of TTC*. Considering the case with H_s=3.75 m, the shape parameter for the stationary case (Distr.1) is close to 2, which means it is similar to a Rayleigh distribution. For the same wave height, the progressive case (Distr.2) has a β value close to 5, which means that it follows a general Weibull case. Considering the case with H_s=4.25 m, both progressive and stationary cases have a shape parameter close to 1, which means that the distributions can be approximated by an exponential distribution. Figure 7 shows the cumulative density functions of the individual distributions for transient, progressive, and stationary state capsizes, together with the Mixed-Weibull one. From this picture, all the aforementioned considerations can be easily visualised. The figure highlights the different progressive and stationary capsize behaviour between the two different wave heights tested.

However, by changing the significant wave height, the nature of the distributions for progressive and stationary capsize also vary, suggesting that the general Weibull model is appropriate to cover the possible distributions of the different capsize modes. Adopting simpler distributions commonly used in naval architecture, such as Rayleigh or exponential models, may lead to appropriate fitting only in some particular cases.

As the number of cases analysed in the test is not enough to characterise the parameters of the individual distribution in such a way as to identify simpler formulations for the capsize cases, the Mixed-Weibull model represents a good fitting proposal for all the possible capsize modes.

5. CONSEQUENCES FOR FLOODING RISK ESTIMATION

The characterisation of TTC* (and consequently TTC) through a Mixed-Weibull allows for the opportunity to consider different kinds of significant values for the TTC*. As mentioned, it is common practice to use the mean among a few repetitions as a significant value for TTC. Here, instead of the mean, different values can be considered, being representative of the analyses of the extreme. From the reported cases, it is evident that a significant part of the capsizes occurs in the transient stage. Thus, this condition is extremely critical for the ship's safety. By considering the mean value of the TTC, leads to a too-optimistic prediction of ship safety.

Such an effect is evident also when the risk of flooding needs to be estimated. In fact, the evaluation of risk through the Potential Loss of Life (PLL) may be strongly influenced by the TTC. By employing a multi-level framework for the evaluation of risk (Vassalos et al. 2023), for the so-called Level-2 prediction, an estimation of the TTC is necessary. In the case of a Level-2.1 prediction, the TTC enters directly into the following empirical formulation for risk:

$$FR = \begin{cases} 0.0 & \text{if } TTC > n \\ 0.8\left(1 - \dfrac{TTC - 30}{n - 30}\right) & \text{if } 30 \le TTC \le n \\ 1.0 & \text{if } TTC < 30 \end{cases} \tag{10}$$

where n is the maximum allowable evacuation time in seconds according to MSC.1/Circ. 1533.

In the case of a Level-2.2 prediction, the TTC needs to be directly compared with the evacuation simulations. In such a case, it is of utmost importance that a reliable value of TTC is used, as the TTC is the time threshold necessary to determine the fatality rate of the analysed evacuation scenario.

Therefore, with a flooding scenario that possibly leads to a transient capsize being much more dangerous than others, the sole adoption of the mean value of multiple repetitions as significant to the risk analysis may lead to an underestimation of the risk itself. As an example, for the case with H_s=3.75 m, the mean value of TTC is 1,160.8 seconds, but considering the extreme events with a percentile of 0.98, the significant TTC drops to 50.5 seconds. With the same assumption, considering H_s=4.25 m, the mean value is 900.0 and the 0.98 percentile is 48.4.

For the cases analysed in this example, a level 2.1 prediction is independent of the TTC, as the TTC is lower than 30 minutes; thus, according to equation (10), the fatality rate *FR* is always equal to 1.0. However, by considering the Level 2.2 prediction, which means a fully direct approach to risk, different TTC led to different fatality rates.

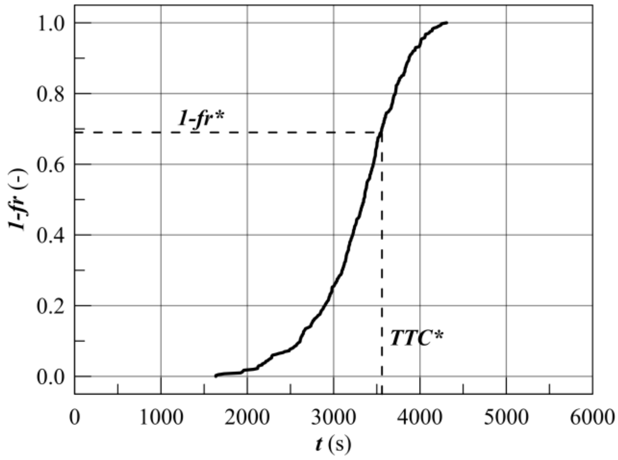

Figure 8: fatality rate estimation from the TTC.

Figure 8 gives an overview of the process necessary to determine the fatality rate from the evacuation analyses curve. Thus, changing TTC induces changes in the *FR* (or 1-*FR* in the graph). This in turn reflects the PLL evaluation, as the risk is given by the following formulation:

$$PLL = p_f \cdot c_f \tag{11}$$

where p_f is the probability of flooding and c_f identifies the consequences of the associated flooding event. The consequences are evaluated from

$$c_f = FR \cdot POB \tag{12}$$

where *FR* is the fatality rate and *POB* is the number of people onboard.

6. CONCLUSIONS

The present paper proposes a novel methodology to determine the Time to Capsize of a damaged ship by applying the extreme value theorem. A Mixed-Weibull model is introduced to capture the three different capsize modes: transient, progressive, and stationary.

Thanks to the application of an evolutionary algorithm, it is possible to automatically fit the 12 parameters needed to characterise the Mixed-Weibull regression model. The provided regressions on two reference cases highlight considerably high goodness of fit, evaluated through both R^2 and R^2_{adj} parameters.

The reference cases have been tested with 100 repetitions per case to capture the random nature of irregular waves. This is a completely different methodology of estimating TTC, namely, employing the mean of 5 repetitions only. As the number of calculations is significantly high, taking into consideration the amount of time needed to perform a calculation, it is not advisable to perform such a detailed analysis for all the cases being analysed within a damage stability framework, but only on a reduced set of critical cases, in such a way as to inform a forensic analysis of the case itself.

The provided methodology highlights cases that are potentially dangerous for the vessel, as transient capsize may still occur whilst in progressive or stationary stage, something that the conventional methods do not detect as only the mean of five repetitions is considered.

Furthermore, being able to characterise the TTC by means of a mixed distribution may allow for future studies aiming at a fully probabilistic estimation of loss of life after an accident, which means convolute the distribution of the time to capsize with the distribution of the time to evacuate obtained by evacuation analyses.

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