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Statistics of extreme hydroelastic response for large ships

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ABSTRACT

For the safety of crew, ship and cargo, it is essential to assess all aspects of the wave loading to ensure that ships are designed to endure extreme events. This paper describes a practical method for prediction of extreme stresses using as an example measured strain in the deck amidships of a container vessel operating in the North Atlantic. The focus is placed on the whipping structural response, which refers to transient vibratory response of the hull girder due to wave impacts occurring mainly in the bow area.

Due to non-stationarity and complicated nonlinearities of the wave induced loads, as well as the human factor in operation of ships, reliable numerical prediction of extreme response, including whipping, is challenging even though significant advances have been made in developing hydro-elastic computational tools in recent decades. Moreover, laboratory tests and numerical simulation tools may not fully reproduce the critical conditions that take place in reality, and these conditions may not even be well understood. Therefore, measurements on real ships provide an opportunity for unique insights into the structural responses when the vessel is at sea.

In addition, a discussion of the ACER (Average Conditional Exceedance Rate) method is provided. It is shown that this method is suitable for practical prediction of extreme values of structural stresses. Unlike methods based on asymptotic extreme value theory, the ACER method explores pre-asymptotic statistics. The latter is of great practical importance for engineering and design. This method opens up for the possibility to predict simply and efficiently both short-term and long-term extreme response statistics, which may also be useful for the captain on board.

The last, but not least is data clustering issue. Whipping process possesses clustering due to its resonance nature; therefore conventional and widely used Poisson assumption is no more valid. ACER method effectively accounts for data clustering, leading to more accurate extreme response estimate, than Poisson assumption methods.

1. Introduction

This paper studies measured hydroelastic response of large container vessel. Hydroelastic loads are represented here with whipping and springing [1].

The Post-Panamax container ship MSC Napoli broke in January 2007. Another Post-Panamax container ship, MOL Comfort broke in June 2013. Although these two ships may not have been designed and approved according to current safety practise resulting in substandard collapse strength compared to other similar ships, both ships broke because of hull girder overloading. MSC Napoli was broken in way of the engine room bulkhead and MSC Napoli was broken amidships in way of a pillar bulkhead. These severe

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accidents affected the industry, in particular the container ship industry. The latter two cases have been intensively followed up by thorough investigations [2,3]. Investigation reports focus on the estimate of the three main load components that may contribute to break such ships in two:

- Still water vertical bending moment due to the ballast and cargo loading
- Wave induced vertical bending moment due to the sea state and relative vessel heading
- Wave induced vibration, i.e. whipping due to bow flare slamming, contributing to increase the vertical bending moment

The investigation reports [2,3] analyzed the collapse strength that has been determined by nonlinear FEM (finite element analysis). The collapse strength must exceed potential loading, but in the two accidents it was clearly not the case. There are many possible elements that could have made the collapse strength dangerously weak. For MSC Napoli, the transverse stiffening without redundancy was a critical element, while for MOL Comfort double bottom bending and reduced buckling strength due to bi-axial buckling was critical.

It can be concluded, that uncertainties are of big importance both on the capacity and the loading side. Especially on the loading side there are big uncertainties, exemplified by the deterministic versus the probabilistic assessment on MSC Napoli, where one appendix of the report [3] suggests that whipping was a key contribution, while another appendix suggests that it is likely contribution, but not necessary an only collapse cause. On MOL Comfort there were significant uncertainties to both the still water bending moment, and to the wave bending moment and whipping. The latter was exemplified also by the assumptions on significant wave height, which was increased from 5.5 m reference to an interim report [2] to 7.5 m.

The International Association of Classification Societies (IACS) has issued recently (as a consequence of these two accidents) new unified requirements for longitudinal strength standard for container ships, URS11A [4] as well as new unified requirements for functional requirements on load cases for strength assessment of container ships by finite element analysis, URS34 [4]. These requirements address the hull girder loading and collapse strength, and URS11A now is including functional requirements to whipping to be addressed on Post Panamax container ships. The latter requirements should be implemented by all class societies, and in some cases the scantlings (steel weight) may increase, but some class societies consider already whipping in the approval. Other class societies have also updated guidelines for whipping, but the different class societies do not have similar or harmonised procedures or tools, therefore the results can differ.

From the above it can be concluded that uncertainties are present and important. One of the major uncertainties is related to the hull girder loads. The latter is the focus of this paper, i.e. the wave loading and the whipping, while the still water loading has not been considered. Rather than using numerical calculations, real stress measurements of a 2800TEU container ship operating in North Atlantic have been considered. Each voyage (crossing) represents a new random process, taking place in different seasons in the years 2007–2010. Assembling all different voyages into one single time process introduces additional non-stationarity. Different authors have being studying statistics of whipping of the same 2800TEU container ship, see for example [5].

Although ship stress statistics in irregular waves can be accurately determined in a well-designed model test, obtaining reliable estimates for the extreme response is challenging. Due to nonlinearity of the response in steep sea states, data from many realizations of a given sea state are often required to obtain robust estimates. In model tests, this is a time consuming and costly process. In many cases only one or a few 3-h realizations are therefore simulated in the model basin or towing tank (head sea only), and the assumptions regarding sea states, loading condition, heading, speed, wave energy spreading and model representation introduce significant uncertainties.

Thus, the real operational data are of great importance, if available. In case the measured dataset is representative, but contains only limited amounts of crossings, the natural question can be asked is how to extrapolate the statistics towards extreme response levels, which have not been crossed by the measured time series. Therefore, there is a substantial need for new statistical approaches to be able to utilize limited non-stationary data sets, and give reasonable prediction of the probability of extreme events. There is also a significant need to investigate the statistical robustness of these estimates in more detail, and, if possible, develop and establish new methods to improve the estimates obtained from a limited data set. The approach adopted in this paper was previously benchmarked in various applications; see [6–8]. A further development of this method was published in [9–12].

An important study was done, based on full-scale measurements obtained from a one year monitoring campaign onboard the Victoriaborg, a general cargo/container vessel [13]. report extreme distribution tail of whipping stress and its low and high pass components which are of similar qualitative tail shape as presented in this study, compare Figs. 5–7 and cumulative distribution of vertical hull girder bending moments plot in [13].

The authors have previously applied the ACER method to ship whipping data [14,15] [16]; and [17], but the current study analyses significantly larger datasets, enabling deeper insights into the extreme value statistics and the importance of whipping versus design rules. The presented approach assesses the extreme response by employing the ACER function combined with an efficient optimization procedure that allows prediction at extreme response levels. The latter is a novel state of art approach and is benchmarked against what is considered to be a robust state-of-the-art method. The main objective of this paper is to come up with improved methods for assessment of extreme response, with special emphasis on whipping.

A typical loaded container TUE ship is presented in Fig. 1. The stress is measured amidships in the longitudinal direction on a flat bar below upper deck. At this location the stress is dominated by vertical bending and whipping. The measurements cover an effective period of two years. Further explanation of the hull monitoring system can be found in [18].

Fig. 1. An example of a loaded Post Panamax container vessel.

2. The whipping phenomenon

Fig. 3 presents an example of a whipping episode. Whipping starts in sagging and decay slowly due to low damping of deck midship port (DMP) stress. Mean stress have been removed. The vibration (whipping) begins in the sagging part of the cycle when the deck is in compression, see Fig. 3. Sagging stress has negative sign (compression in deck), while hogging stress has positive sign (tension in deck).

This happens normally when the bow is diving into a steep wave, which consequently causes a bow flare impact with water spray, water on deck level and green water in extreme cases. Because of low damping the vibration continues also into the WF hogging cycle. The hogging part of the cycle is often of interest, because the dynamic hogging is added to the static hogging from the still water loading, a condition considered as a major reason for the collapse of the container vessel MSC Napoli [3].

Note that Fig. 3 exhibits narrow band oscillation pattern, which is one of the kinds of clustering – see further down in this paper about issue of de-clustering of measured data.

Fig. 2 (a), (b) present the power spectral density (PSD) of the DMP stress $\sigma(t)$ in rad/s and Hz, respectively. It exhibits a response peak at a high frequency (HF) in Fig. 2 (a), approximately equal to 4.6 rad/s (i.e. about 0.73 Hz or 1.37 s). The total measurement time T is about 2 years, which is the duration of the global time series, obtained by gluing together all individual time series. The mean stress value, equal to 12.5 MPa, was subtracted from this global stress time series.

Smaller higher-order vibration has also been observed at about twice this frequency. The first frequency peak (4.6 rad/s) in Fig. 2 (a) is related to the vertical 2-node vibration, which is the governing vibration mode, while the second peak at 9.5 rad/s is possibly the horizontal 2-node vibration mode.

At the same time the WF spectrum peak for this case has a sharp peak which is located at about 0.3 rad/s (i.e. 0.048 Hz or 20.9 s) in Fig. 2 (a). The WF peaks represents the encounter frequency which depends on the heading and speed of the vessel, i.e. the wave period would differ. This first sharp peak could come from following sea in forward speed and the real wave period would then be lower. There is also a second peak at about 0.7 rad/s (i.e. 0.11 Hz or 9.0 s), which is more likely coming from head seas in forward speed, and the real wave period would then longer.

Assuming the speed would be 19 knots towards North America and 0.7 rad/s comes from head sea, then the wave period is about 13 s. If the vessel goes at 15 knots to North Europe and the sea is following, then the first peak would also correspond to a wave period of 13 s. It is known that the waves tend to go from North America to North Europe on this North Atlantic trade. However, swell could affect this as well as heading distribution and possible warping stress from torsional response that is related to roll period which is often in the order of 20 s also for this vessel, corresponding to the first peak. In any case two peaks should be expected in the WF response even without swell due to the “Doppler” effect explained above.

It should be noted that high-frequency whipping usually happens in head seas. For these two lower frequency peaks discussed above, at about 0.3 rad/s and about 0.7 rad/s in Fig. 2 (a), one peak could be due to following seas while the other could be swell.

Fig. 4 presents layout of mid ship cross section, with measurement position indicated.

3. Sea state statistics

The global wave statistics is based on North Atlantic (NA) and World Wide (WW) scatter diagrams [18,19].

The whipping stress time series, analyzed in this paper, can be regarded as the ship dynamic system output (response), while the wave load is a stochastic input. Therefore, each sea state represents a short term stationary part in the long term (total voyage) response time series. Port time intervals are neglected. One needs to assume that the measured dataset is representative on both a

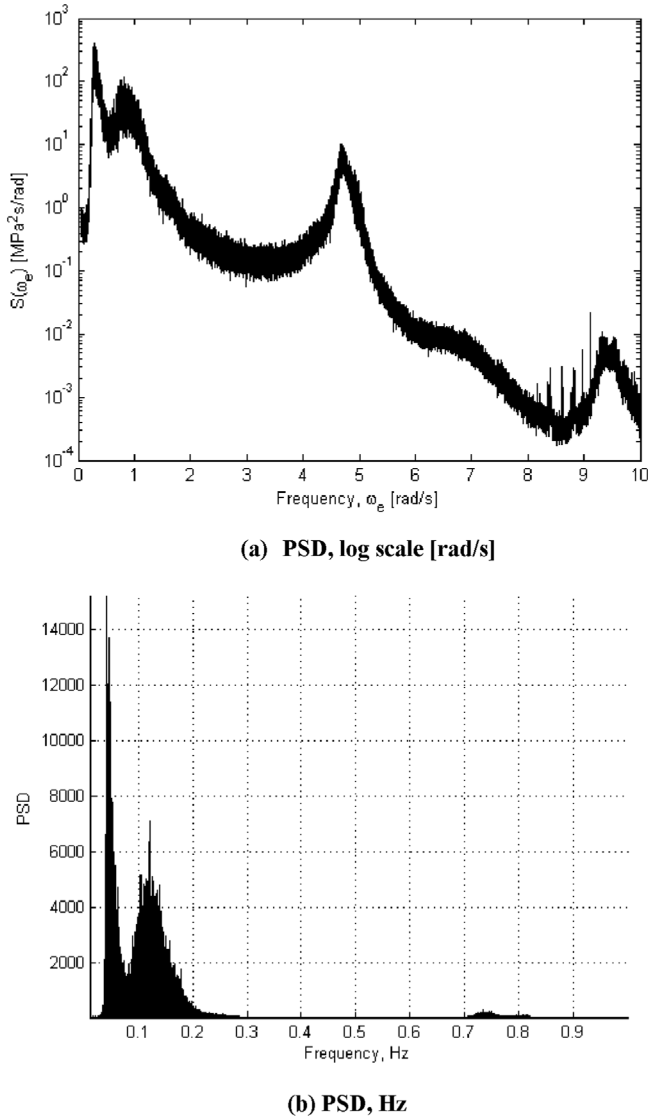

Fig. 2. PSD of measured DMP stress.

short and long term scale. The latter assumption can be justified by taking a large number of single voyages and assuming that global trends (as for example global climate change) can be neglected. It is important to mention that the most severe seas with the highest waves are not necessarily the most extreme for the whipping response, which can be more substantial when the vessel speed is high. For the higher sea states in head seas, the vessel speed decreases, and at around 10–12 m significant wave height, the vessel will not be able to maintain steering capacity and forward speed in head seas. That is also one reason for avoiding the severe storms in head seas, and it will affect the routing as the estimated time to arrival (ETA) will be delayed significantly.

4. The statistical approach

The statistical predictions given in this paper, are only valid for a given vessel with the given cruise route and period. Still, the proposed statistical method is general, and it highlights the mechanical nature of the whipping stress distribution in the extreme tail. The latter is of practical importance for a large variety of container ships and voyage routes.

Since statistics of the encountered sea states and extreme responses can be affected by applied routing system and captains decisions, it is worth mentioning that voyages analyzed in this paper correspond to a similar routes, therefore route deviation bias was not analyzed.

The ACER method [12] is applied to analyze the measured data in order to assess the extreme value statistics. The major advantage of the ACER method is that it utilizes the full non-stationary data set. Moreover, this method accounts for data clustering, inherent in the whipping phenomenon.

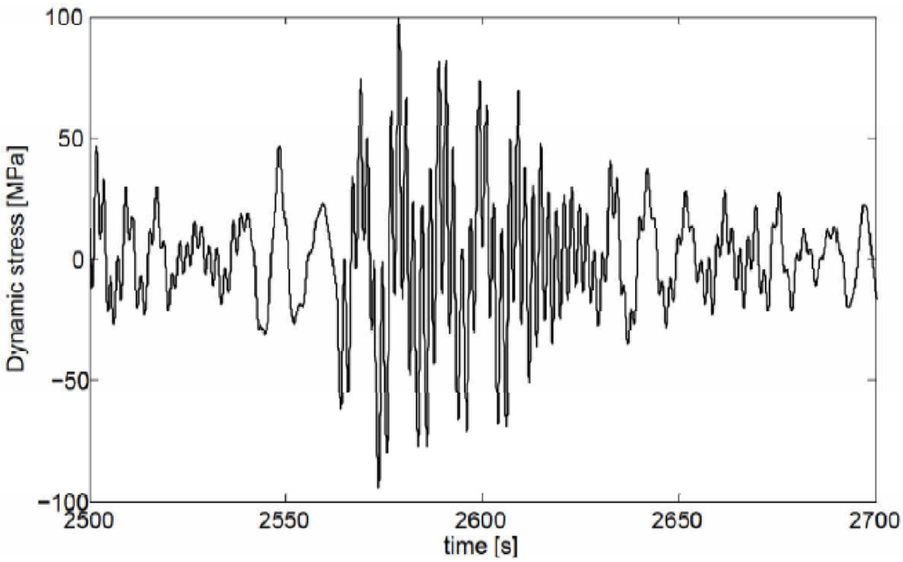

Fig. 3. Whipping starts in sagging and decay slowly due to low damping of deck midship port (DMP) stress. Mean stress have been removed. Hogging is positive, sagging is negative.

Obviously, some of the 70 voyages contain transient whipping processes in clustering, and these processes are of different levels of whipping in terms of the severity of stormy seas, direction and speed of vessels. Hence, even assuming that these whipping processes are homogeneous in hydrodynamics and structural dynamics without accounting for nonlinearities, their levels of ergordicity are different. However, none of statistical method is universal and each one has its own assumptions and limitations. The paper was an attempt to properly analyze a unique data set, which was not previously analyzed to the extent of over 2 years total duration.

Let $M(T) = \max\{Z(t): 0 \leq t \leq T\}$ be the extreme value of the response process $Z(t)$ over a long-term time interval with length T. The stress response process $Z(t)$ is obviously non-stationary, because of different sea states, headings and loading conditions apply during the voyages. In order to draw statistical conclusions from the measured data, one needs to assume some form of ergodicity locally. The latter means that (since only one time series of data is available) the statistical information one needs, can only be drawn from time averages obtained from this single time series. The process of extracting statistical information from the total measured time series available would be to consider the environmental conditions met by the vessel during the voyages as a sequence of stationary 3 h sea-states. Assuming that the vessel speed and heading is kept constant during each sea-state, the response time history during each of the 3 h sea-states can be used to extract short term statistical information under an ergodicity assumption. The required long term statistics, including the effect of the vessel's loading condition, is then obtained by a second time averaging process.

Still, it worth noting that for harsh conditions with large whipping loads, the ergodicity assumption may not be accurate within a 3 h period. The remedy is then to use a large number of independent voyages, each one about one week duration, then ergodicity can be captured locally on that larger (weekly) time scale. This paper analyses over 70 trans-Atlantic voyages, which may be regarded as sufficient to treat the dataset as locally ergodic even for extreme whipping events. Note that the ACER method does not rely on the choice of the short term duration, given that the dataset is large enough.

The actual time series X_j that is used to represent the response process $Z(t)$ for the specific analysis carried out, can be different from the process itself. Since our focus in this paper is on the extreme response, we may choose to analyze either the sampled response process itself or the time series of extracted peak response values (by "peaks" authors mean local maxima in the response time series). Whichever time series is used, the long term extreme value distribution of $M(T)$, based on the ACER function of order k, can now be expressed in the following manner.

$$P_k(\eta) \approx \exp\left(-(N-k+1)\hat{\varepsilon}_k(\eta)\right) \tag{1}$$

Where

$$\hat{\varepsilon}_k(\eta) = \frac{1}{N-k+1}\sum_{j=k}^{N} a_{kj}(\eta) \tag{2}$$

$\hat{\varepsilon}_k(\eta)$ represents the empirical ACER function of order k. Note that the total number of data N depends on the time series used; with $a_{kj}(\eta) = \mathbb{E}[A_{kj}(\eta)]$ where $A_{kj}(\eta) = 1\{X_j > \eta, X_{j-1} \leq \eta, ..., X_{j-k+1} \leq \eta\}$, $j = k, ..., N$, $k = 2, 3, ...$.

Because the extreme value distribution based on the concept of mean level upcrossing rate may be more familiar than the one based on the ACER functions, it is expedient to tie the connection between the two concepts. The long term extreme value distribution of $M(T)$ based on the assumption of a nonhomogeneous Poisson process for the upcrossings of high response levels is given as

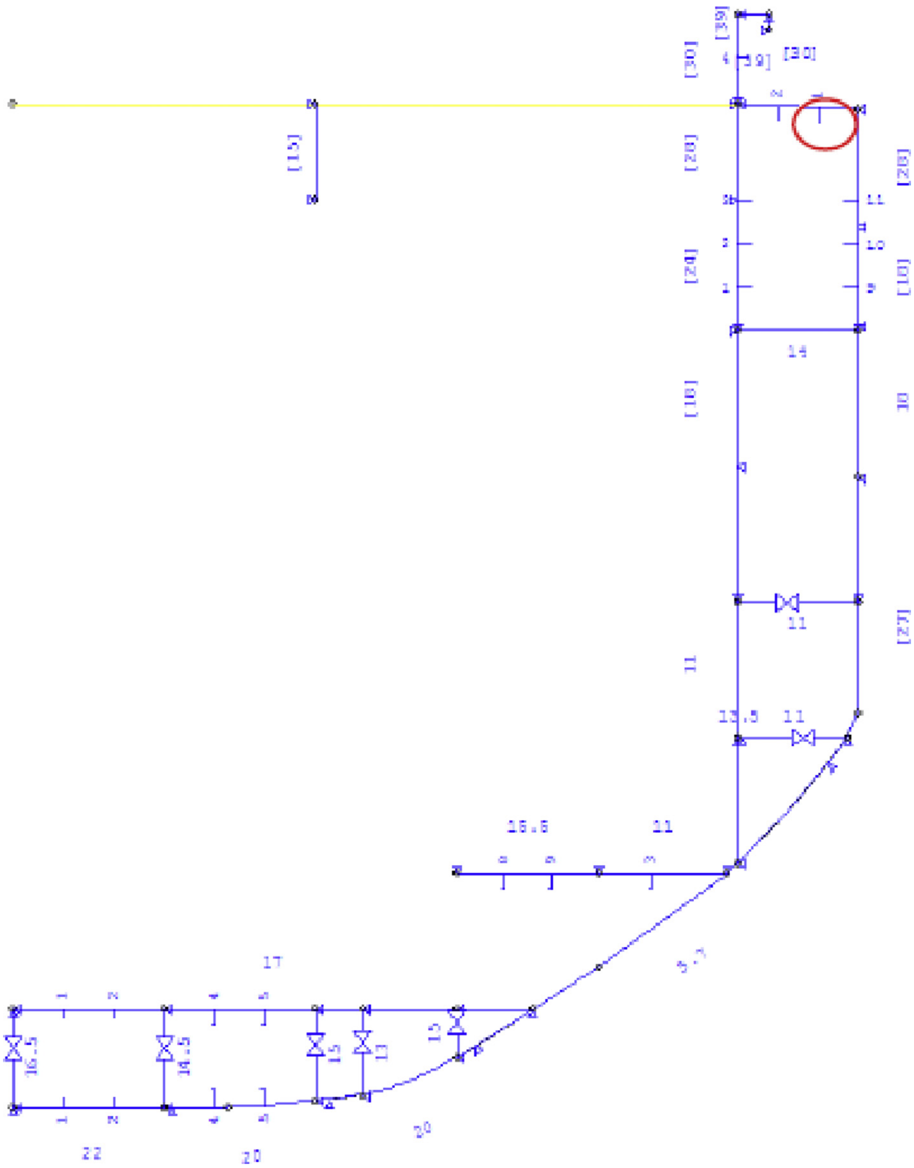

Fig. 4. Layout of mid ship half cross section, with measurement position indicated by the red circle. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

$$Prob(M(T) \leq \eta) \approx \exp\left(-\int_0^T \nu^+(\eta;\, t)\, dt\right) = \exp\left(-\nu^+(\eta)\, T\right) \tag{3}$$

where $\nu^+(\eta;\, t)$ denotes the mean upcrossing rate of the response level η at time t, while $\nu^+(\eta) = \int_0^T \nu^+(\eta;\, t)\, dt/T$ denotes the time averaged mean upcrossing rate. For the application in this paper, this can be clarified further. Let us assume that for the whole long term time series, the totality of unique stationary conditions for the ship during its voyages can be assembled in an array of parameter vectors $\boldsymbol{w}_j$, $j = 1, \ldots, M$. Each $\boldsymbol{w}_j$ contains the parameters describing the condition for the ship during a 3 h stationary sea state. Then equation (3a) can be expressed as follows,

$$Prob(M(T) \leq \eta) \approx \exp\left(-T \sum_{j=1}^{M} \nu^+(\eta;\, \boldsymbol{w}_j)\, (T_j/T)\right) \tag{3b}$$

where $\nu^+(\eta;\, \boldsymbol{w}_j)$ denotes the constant mean upcrossing rate for condition $\boldsymbol{w}_j$, T_j denotes the amount of time the ship is in condition $\boldsymbol{w}_j$ during the total time T. Therefore, T_j/T expresses the fraction of total time that the ship is in condition $\boldsymbol{w}_j$. Equations (3a) and (3b) are two typical ways of expressing the long term extreme value distribution based on the mean upcrossing rate, cf [20].

The connection between the upcrossing rate and the ACER functions is obtained by recognizing that if the time series X_j represents the sampled full response process, then the ACER function of order 2, $\tilde{\varepsilon}_2(\eta)$, is identical to the time averaged upcrossing rate except for normalization: the upcrossing rate is per time unit, while the ACER function is per data point. In this paper, however ACER was used on the local peaks, extracted from time series, therefore in that case ACER function of order 2 differs from mean upcrossing rate in its nature. The main advantage of using ACER function of order 2 and higher is that it enables accounting for data de-clustering, while mean upcrossing rate is relying on Poisson assumption and therefore may overestimate extreme response due to dependency of neighboring peaks (data clustering).

For the purpose of estimating the extreme value distribution of the kind of data studied in this paper, it is normally convenient to focus on the time series of peak response values. The cause is that the dependence structure in the response process is more directly displayed by using the time series of peak values. Hence, in the following the discussion is limited to this time series. In this case, $N\,\hat{\varepsilon}_1(\eta)$ denotes the expected number of peaks above the response level η during the time T, where N denotes the total number of peaks in the time series. Since there may be more than one peak between two upcrossings, it is clear that $\nu^+(\eta)\,T \le N\,\hat{\varepsilon}_1(\eta)$. On the other hand, in the estimation of $\hat{\varepsilon}_2(\eta)$, a group of consecutive peaks exceeding the level η will be counted as one exceedance. From this it follows that $(N-1)\,\hat{\varepsilon}_2(\eta) \le \nu^+(\eta)\,T$. In general, $(N-k)\,\hat{\varepsilon}_{k+1}(\eta) \le (N-k+1)\,\hat{\varepsilon}_k(\eta)$. In some cases $(N-k+1)\,\hat{\varepsilon}_k(\eta)$ is significantly less than $\nu^+(\eta)\,T$, which means that equation (3a) may lead to overly conservative extreme value estimates. However, for the application in this paper, we shall see that equations (3a) and (3b) in fact lead to quite accurate estimates of the total extreme values, while there is a small deviation for estimates limited to only the whipping response. The latter is due to the fact that whipping is a strongly resonant response where the peaks are highly correlated.

5. Extrapolation method

This section discusses the important issue of extrapolating the chosen ACER curve towards extreme response levels with low probability. The authors apply the Naess-Gaidai extrapolation method [8], which suggests the following parametric form for the tail ACER function

$$\hat{\varepsilon}_k(\sigma) \approx q\cdot exp(-a(\sigma-b)^c), \ldots \sigma \ge \sigma_0 \tag{4}$$

with σ being the response level, which is stress in the case of this paper; $a,\ b,\ c,\ q$ are suitable tail constants; σ_0 is a suitable tail marker ($\sigma_0 = 30$ MPa in Figs. 8 and 12), indicating the start of the fit based on equation (4). Thus by plotting $ln\{ln(\hat{\varepsilon}_k(\sigma)/q)\}$ versus $ln(\sigma-b)$, it is expected that almost perfectly linear tail behaviour will be obtained.

It is suggested to do the optimization on the log-level by minimizing the following mean square error function F with respect to four arguments $a,\ b,\ c,\ d$.

$$F(a,\ b,\ c,\ d) = \int_{\sigma_0}^{\sigma_1} w(\sigma)\{ln(\hat{\varepsilon}_k(\sigma)) - \ln q + a(\sigma-b)^c\}^2\,d\sigma \tag{5}$$

where σ_1 is a suitable data cut-off value, i.e. the largest response value, where the confidence interval width is still acceptable. The weight function w is defined as $w(\sigma) = \{lnC^+(\sigma) - lnC^-(\sigma)\}^{-2}$ with $(C^-(\sigma),\ C^+(\sigma))$ being a 95% CI (confidence interval), empirically estimated from measured data.

It is shown that the Naess-Gaidai extrapolation (4) is a robust and efficient extrapolation tool for a wide variety of random processes in maritime and offshore engineering, see [6–11,17]. In [14,15] the authors have already validated the ACER method, applied to whipping data, versus other relevant statistical methods, such as the Gumbel and Weibull fit. It was shown that ACER extrapolation provides more accurate prediction in terms of confidence intervals, than other conventional methods.

6. Response statistics

This section presents results of the statistical analysis of the measurements of the deck stress on the port side amidships (DMP), taken from over 70 North Atlantic voyages in the period 2007–2010. The Naess-Gaidai fit (4) is applied to the $\hat{\varepsilon}_2(\sigma)$ functions, since $\hat{\varepsilon}_k(\sigma)$ has converged to $\hat{\varepsilon}_2(\sigma)$ for $k > 2$.

The mean value varies with loading conditions and also during a voyage due to de-ballasting, and the mean value should be removed. However it is slightly wrong to filter away the mean value instead of removing the still water bending stress. The mean value at any time record, i.e. half hour, was removed before the long term time series was merged. Then removing the mean by filtering implies that the asymmetry in the response and also the forward speed effect giving a steady small sagging moment contribution is removed. This forward speed effect is a stochastic process and it should be included in the dynamic part. Removing mean per for example, voyage is not OK.

It is seen from Fig. 2 that significant response PSD is located at about 0.3 rad/s and 0.7 rad/s, while the smaller peak around 4.7 rad/s indicates whipping (and springing). The width of the whipping and springing peak is affected by different loading conditions on the east and west bound voyages and thereby different natural frequencies.

The mean up-crossing rate ν^+ and the $ACER_2$ (which is ACER second order function) curves are plotted for comparison in Figs. 5–7, and Figs. 9–11. By multiplying ν^+ with the total time duration T and $ACER_2$ with total number of peaks N, one can scale the y-axis to the 25 year exceedance probability levels. This is done in Figs. 5–12, therefore the y-axis (vertical) value of 1 corresponds to the 25 year return period level. Predicting response levels with 25 years return period is particularly important for ship design. The

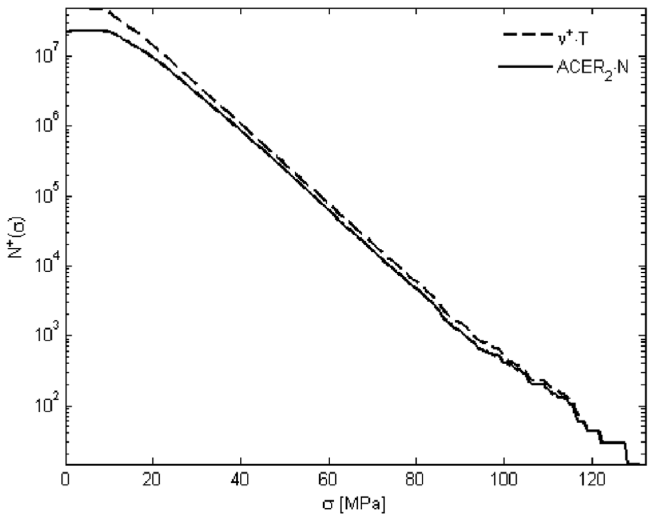

Fig. 5. Sagging stress up-crossing (–) and $ACER_2$ (−) with whipping included.

DMP stress response $\sigma(t)$ is measured in MPa. Sagging stress has negative sign (compression in deck), but for plotting in section 6.1, the negative sign was swapped to positive. In order to study whipping in more detail, high and low pass filtering was performed, with cut-off frequency at 0.4 Hz. Therefore, the high pass signal contains whipping, while the low pass signal does not, see Fig. 2 (b).

6.1. Sagging stress statistics

Fig. 5 presents sagging stress statistics, specifically the mean up-crossing rate and the $ACER_2$ second order function on the log scale. Both mean up-crossing rate and the $ACER_2$ function are multiplied by N, and denoted $N^+(\sigma)$. N is chosen to be the total number of local peaks in 25 year period. The latter gives the target level for extrapolation equal to $10^0 = 1$, see Figs. 8 and 12.

Fig. 6 presents ACER and crossing rate functions, based on the low-pass (LP) filtered sagging. LP filtering was done at a cut-off frequency of 0.4 Hz (=2.5 rad/s), having the purpose of removing whipping (and springing). Fig. 7 presents high-pass (HP) filtered sagging; HP filtering was done at a switch-on frequency of 0.4 Hz.

Fig. 8 presents extrapolation (NG) of $ACER_2$ function for sagging; it is seen that ACER extrapolation fits well over the wide data range. 95% Confidence Interval (CI) is indicated by dashed lines and its extrapolation by dotted lines. The data tail is cut near stress value about 105 MPa, since confidence bands have exceeded the corresponding ACER value, making those data points unusable for extrapolation. Horizontal dotted line indicated 25 year return period of interest.

In Figs. 8 and 12 both dashed (CI) lines are cut off at the response level, when CI width exceeds the expected value itself, since then log gets negative argument. Note that for the CI (as well as for the ACER function itself) extrapolation, the very tail part was not taken into account, due to its high inaccuracy; instead the up-tail data (with much more narrow CI) was used as a base for

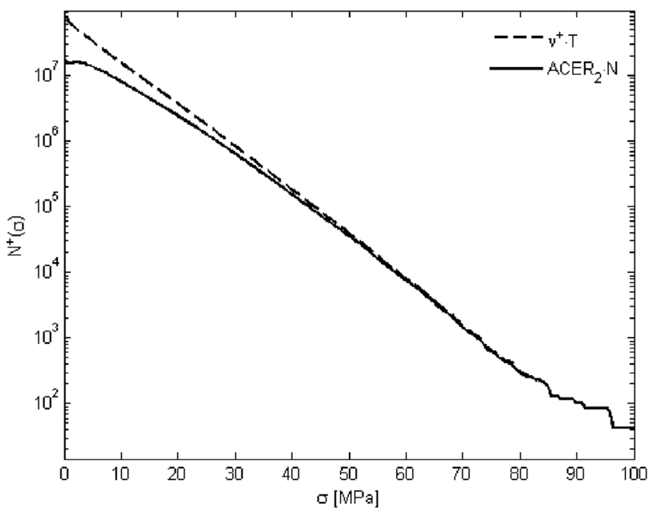

Fig. 6. Low pass filtered sagging stress $ACER_2$ and up-crossing (dashed line).

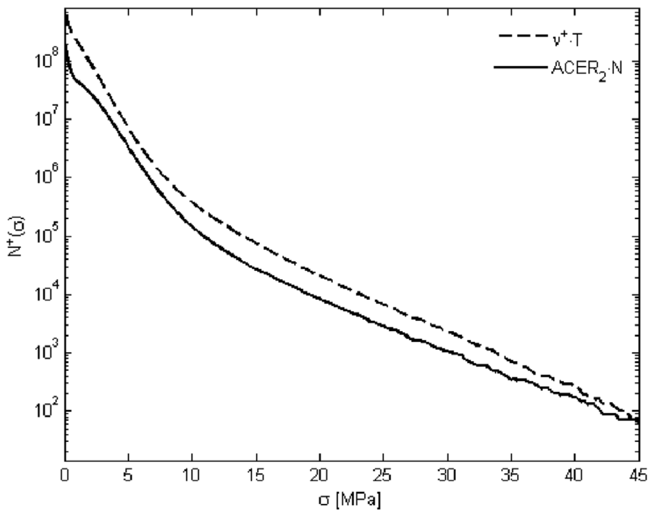

Fig. 7. High pass filtered sagging stress ACER$_2$ and up-crossing (dashed line).

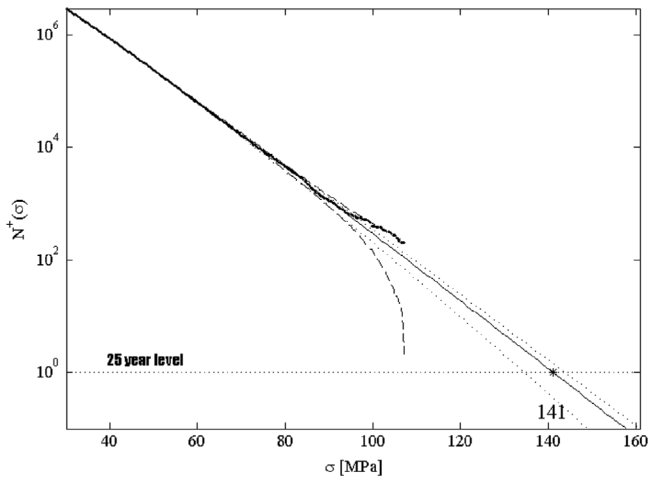

Fig. 8. Tail extrapolation for sagging, see Fig. 5, including whipping. 95% CI is indicated by dashed lines and its extrapolation by dotted lines.

extrapolation.

6.2. Hogging stress statistics

Fig. 9 presents hogging stress statistics, specifically the mean up-crossing rate and the ACER$_2$ function on the log scale. Fig. 10 presents the mean up-crossing rate and the ACER$_2$ function based on low-pass (LP) filtered hogging. LP filtering was done at a cut-off frequency of 0.4 Hz (=2.5 rad/s), having the purpose of removing whipping (and springing). See Fig. 11.

Fig. 12 presents extrapolation of the ACER$_2$ function for hogging; it is seen that ACER extrapolation fits well to the wide data range. The 95% Confidence Interval (CI) is indicated by dashed lines and its extrapolation by dotted lines. The data tail is cut where confidence bands are exceeded, at the stress value about 90 MPa. The horizontal dotted line indicates the 25 year return period of interest.

6.3. Statistical summary

The proposed extrapolation method, based on equation (4), already proven in a wide range of applications to be quite accurate in predicting extreme values, has been applied. As shown in Figs. 8 and 12, a significant part of the tail statistics is well captured, enabling robust prediction towards higher response levels. The only underlying assumption for the proposed method is regularity of the statistical tail. The proposed extrapolation formula fits well with the measured data. The 25-year return period stress values for sagging and hogging, with and without whipping are given in Table 1. The whipping-induced stress is removed if the low-pass filtering is used, and is included if the high-pass filter is applied.

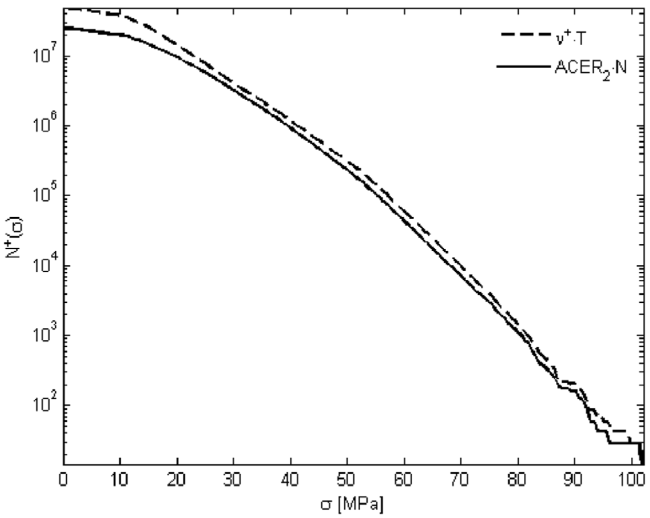

Fig. 9. Hogging stress up-crossing (–) and $ACER_2$ (−) with whipping included.

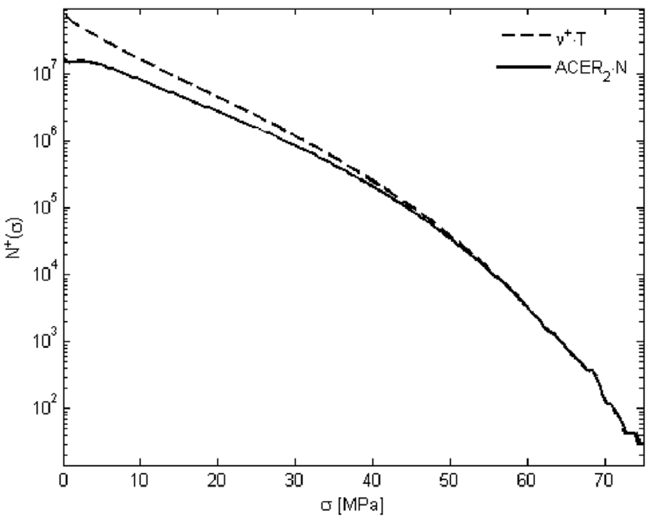

Fig. 10. Low pass filtered hogging stress up-crossing (–) and $ACER_2$ (−).

Table 2 presents comparison of the 25 years design values (i.e. 25-year return period stress values), based on the IACS URS11 vertical bending moment values with those estimated by the ACER method. Given that the ACER extrapolation seems to be accurate, Table 2 suggests that the URS11 (older standard) sagging moment was non-conservative. This suggests therefore that the URS11A (newer standard) is better; however the new sagging moment in URS11A appears overly conservative. The latter conclusion seems reasonable, knowing that some of the software tools tend to produce very high nonlinear sagging moments, and these tools have been used by IACS in development of the new URS11A. It should however be pointed out that some asymmetry in the nonlinear signal may be lost when the time series is filtered to remove the mean. I.e. the sagging values becomes slightly smaller and the hogging values slightly larger. Still the URS11A sagging moment is dramatically above these measurements. The fact that the ACER sagging results is larger than URS11 is not strange, since the 141.3 includes whipping and URS11 does not. It should be noted that the criticism of URS11A sagging in this case is based on measurements of only one container ship. It is therefore necessary to repeat this on more container ships.

Regarding IACS URS11 and URS11A results, with respect to the ACER method predictions. The 25-year largest vertical bending moment (obtained from the ACER method for the bending moment measurements) was used to obtain the stress at the target location and then compare it with the 25-year stress obtained using ACER for stress measurements. IACS URS11 and URS11A were using the same nonlinear structural analysis, since the same structural analysis method should be used when applying statistical extrapolation method, like ACER.

Since the slamming and whipping occur normally in sagging condition (see Fig. 3), the increase of sagging moment then is larger than hogging. Therefore Table 2 indicates the significance of whipping, since the predicted sagging stress by ACER is about one third

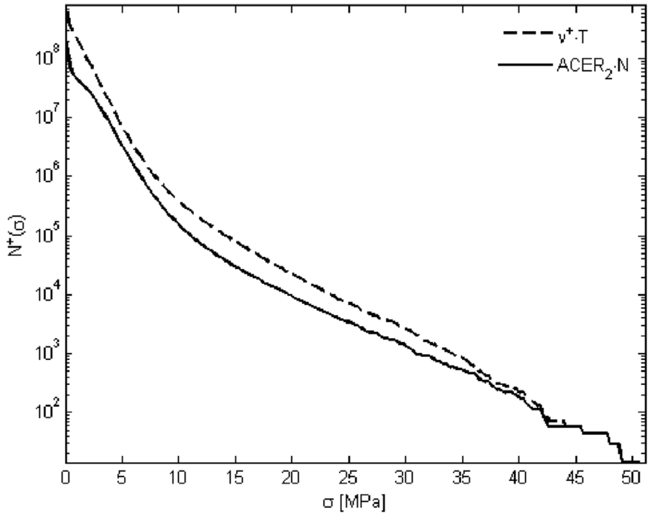

Fig. 11. High pass filtered hogging stress up-crossing (–) and $ACER_2$ (−).

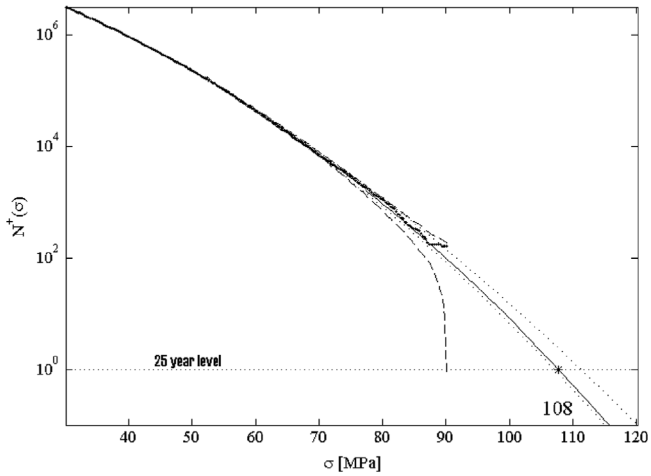

Fig. 12. Tail extrapolation for hogging, see Fig. 9, including whipping. 95% CI is indicated by dashed lines and its extrapolation by dotted lines.

Table 1
Predicted response corresponding to 25-year return period, [MPa], mean stress 12.5 MPa subtracted.

	Total stress unfiltered	Low Pass filtered	High Pass filtering
Sag	141.3	115.5	65.6
Hog	108.0	90.7	63.7

Table 2
Total unfiltered stress comparison, [MPa].

	ACER	URS11A	URS11
Sag	141.3	217.2	121.9
Hog	108.0	110.6	103.6

larger than the hogging stress.

Note that reference to IACS values in Table 2 are not based on any specific statistical method, like e.g. ACER or Weibul og Gumbel etc. or computed through nonlinear structural analysis. IACS values are simply based on the IACS prescriptive formula, developed by IACS [4]. The point is that IACS offers its recommended design value, and the measurements indicate that this is not necessarily a best hit for a ship actually in the North Atlantic, which is IACS's intended design area when looking at IACS Rec. 34 as defines a North

Atlantic scatter chart (URS11 does not actually define the North Atlantic once). It is no more complicated than that, and how the IACS has come to its worth is a completely different story, which is beyond this paper scope. IACS URS11 and URS11A are the most relevant references for extrapolation.

7. Conclusions

This paper studies measured stress time series for a container vessel during her 70 voyages across the North Atlantic during the period 2007–2010. Extreme value statistics of stress was analyzed with and without hydroelastic effects (whipping and springing).

The ACER method was used to extrapolate the distribution tail to the 25-year return period. The ACER method is implemented by expressing the extreme value distribution in terms of the conditional exceedance rate. By fitting a parametric function to the empirical exceedance rate, it is shown that the tail behaviour of the empirical extreme value distribution can be accurately captured. The fitting is based on a procedure that puts more weight on the empirical estimates the more accurate they are. This implies that large “outliers” will not influence very much the fitted up-crossing rate function. It is also noted that the obtained extreme value distribution may deviate somewhat from a Gumbel distribution, indicating that the observed extreme values are not large enough to accurately fit the asymptotic form. The ACER method has been validated by application to a wide range of simulation models with satisfactory predictions [7].

This study found that

- The ACER method captures extreme tail statistics well for both sagging and hogging.
- The ACER method accounts for data clustering, unlike the mean upcrossing rate approach, which is based on the Poisson assumption. In whipping data, clustering plays an important role and must be accounted for.
- With whipping, the deck stresses under sagging are larger than those under hogging.
- Without whipping, the deck stresses under sagging and hogging are close.
- For the investigated vessel, the extrapolated 25-year return period level is 16% higher in sagging and 4% higher in hogging compared with design values specified in IACS URS11 (older standard). This suggests that the older standard may underpredict stresses.
- The newer standard URS11A predictions are 54% higher in sagging and 2% higher in hogging, compared to extrapolated values, suggesting that URS11A is on the conservative side. The method also suggests that clustering is important for this vessel, especially at lower response levels.

When it comes to validation of ACER method based on short term statistics, in order to validate use and accuracy of ACER method for the long term statistics, one can be referred to see [8], where the latter study was carried out for the Naess-Gaidai method for synthetic data. Generating similar stationary short-term measured data is difficult, as one can not easily confirm that one has the same vessel speed, heading, sea mode.

Note also that there is no analysis other than data analysis of measurements behind, and there is no advanced analysis behind the IACS values, apart of just using recommended IACS design values.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.marstruc.2018.05.004.

References

[1] Bishop RED, Price WG. Hydroelasticity of ships. Cambridge University Press; 1979.
[2] ClassNK. Investigation report on structural safety of large container ships The investigative panel on large container ship safety, September 2014 2014http://wwwclassnk.or.jp/hp/pdf/news/Investigation_Report_on_Structural_Safety_of_Large_Container_Ships_EN_ClassNK.pdf.
[3] MAIB. Report on the investigation of the structural failure of MSC Napoli English channel on 18th January 2007 Southampton, UK: Marine Accident Investigation Branch (MAIB), Carlton House, Carlton Place; 2008. SO15 2DZ, Report No. 9/2008, April 2008 https://www.gov.uk/maib-reports.
[4] IACS. URS11 and URS11A. 2015http://www.iacs.org.uk/publications/publications.aspx?pageid = 4&sectionid = 3.
[5] Mao W, Ringsberg J, Rychlik I. The effect of whipping/springing on fatigue damage and extreme response of ship structures. 29th international conference on ocean, offshore and Arctic engineering. 2010. p. 123–31.
[6] Naess A, Stansberg CT, Gaidai O, Baarholm R. Statistics of extreme events in airgap measurements. J Offshore Mech Arctic Eng 2009;131.
[7] Naess A, Gaidai O. Monte Carlo methods for estimating the extreme response of dynamical systems. J Eng Mech ASCE 2008;134(8):628–36.
[8] Naess A, Gaidai O, Haver S. Efficient estimation of extreme response of drag-dominated offshore structures by Monte Carlo simulation. Ocean Eng 2007;34:2188–97.
[9] Gaidai O, Stansberg CT, Naess A. Airgap statistics for a tension leg platform. J Offshore Mech Arctic Eng 2014;137(1).
[10] Gaidai O, Krokstad JR. Extreme response statistics of fixed offshore structures subjected to ringing loads. J Offshore Mech Arctic Eng 2014;136(3).
[11] Naess A, Gaidai O, Batsevych A. Prediction of extreme response statistics of narrow-band random vibrations. J Eng Mech 2010;136(No 3):290–8.

[12] Naess A, Gaidai O. Estimation of extreme values from sampled time series. Struct Saf 2009;31(No 4):325–34.
[13] Aalberts PJ, Nieuwenhuijs M. Full scale wave and whipping induced hull girder loads. 4th. Int. Conf. On hydroelasticity, Wuxi, China. 2006.
[14] Gaidai O, Storhaug G, Naess A. Extreme value statistics of whipping response for large ships. PRADS proceedings. Practical design of ships and other floating structures, vol. 2. 2010. p. 1210–21.
[15] Gaidai O, Storhaug G, Naess A. Extreme value statistics of ship rolling. PRADS proceedings, practical design of ships and other floating structures, vol. 2. 2010. p. 457–66.
[16] Andersen IMV, Jensen JJ. Measurements in a container ship of wave-induced hull girder stresses in excess of design values. Mar Struct 2014;37:54–85.
[17] Storhaug G, Andersen IMV. Extrapolation of model tests measurements of whipping to identify the dimensioning sea states of container ships. ISOPE proceedings. 2015.
[18] Storhaug G, Moe E, Lopes TAP. Whipping measurements onboard a midsize container vessel operating in the North Atlantic. RINA, CMP & SSNAME, int. Symp. on ship design & construction. 2007. p. 55–70.
[19] DNV. Fatigue assessment of ship structures. DNV classification note 30.7, July, 2005. 2005.
[20] Naess A, Moan T. Stochastic dynamics of marine structures. Cambridge University Press; 2013.