This may be the author's version of a work that was submitted/accepted for publication in the following source:

Perez, Tristan
(2015)
Ship seakeeping operability, motion control, and autonomy - A Bayesian perspective.
In Blanke, M & Galeazzi, R (Eds.) Proceedings of the 10th IFAC Conference on Manoeuvring and Control of Marine Craft MCMC 2015 [IFAC-PapersOnLine, Volume 48, Issue 16].
International Federation of Automatic Control (IFAC), Austria, pp. 217-222.

This file was downloaded from: https://eprints.qut.edu.au/90199/

© Copyright 2015 Elsevier

This work is covered by copyright. Unless the document is being made available under a Creative Commons Licence, you must assume that re-use is limited to personal use and that permission from the copyright owner must be obtained for all other uses. If the document is available under a Creative Commons License (or other specified license) then refer to the Licence for details of permitted re-use. It is a condition of access that users recognise and abide by the legal requirements associated with these rights. If you believe that this work infringes copyright please provide details by email to qut.copyright@qut.edu.au

Notice: Please note that this document may not be the Version of Record (i.e. published version) of the work. Author manuscript versions (as Submitted for peer review or as Accepted for publication after peer review) can be identified by an absence of publisher branding and/or typeset appearance. If there is any doubt, please refer to the published source.

https://doi.org/10.1016/j.ifacol.2015.10.283
Ship Seakeeping Operability, Motion Control, and Autonomy - A Bayesian Perspective

Tristan Perez*

* School of Electrical Eng. and Comp. Sc., Queensland University of Technology, Australia. (e-mail: Tristan.Perez@qut.edu.au)

Abstract: Ship seakeeping operability refers to the quantification of motion performance in waves relative to mission requirements. This is used to make decisions about preferred vessel designs, but it can also be used as comprehensive assessment of the benefits of ship-motion-control systems. Traditionally, operability computation aggregates statistics of motion computed over the envelope of likely environmental conditions in order to determine a coefficient in the range from 0 to 1 called operability. When used for assessment of motion-control systems, the increase of operability is taken as the key performance indicator. The operability coefficient is often given the interpretation of the percentage of time operable. This paper considers an alternative probabilistic approach to this traditional computation of operability. It characterises operability not as a number to which a frequency interpretation is attached, but as a hypothesis that a vessel will attain the desired performance in one mission considering the envelope of likely operational conditions. This enables the use of Bayesian theory to compute the probability of that this hypothesis is true conditional on data from simulations. Thus, the metric considered is the probability of operability. This formulation not only adheres to recent developments in reliability and risk analysis, but also allows incorporating into the analysis more accurate descriptions of ship-motion-control systems since the analysis is not limited to linear ship responses in the frequency domain. The paper also discusses an extension of the approach to the case of assessment of increased levels of autonomy for unmanned marine craft.

Keywords: Ship performance assessment, probabilistic methods, motion control.

1. INTRODUCTION

Seakeeping theory studies the motion of surface vessels in waves, and seakeeping analysis is a procedure for computing vessel performance metrics related to the envelope of missions and environmental conditions in which the vessel is to operate (Lloyd, 1998). This analysis is often conducted during the vessel design stage, and the result is a number in the range from 0 to 1 called Operability (O) (NATO, 2000). This number is often given the interpretation of either a frequency, or the proportion of time that a vessel will remain operable. The metric O is used, for example, by Navies as a tool for risk management during procurement to compare the merits of competing vessel designs against a prescribed performance standard—see for example RAN (2003). It has also been argued that increase on operability provides a key performance indicator of ship-ride control systems—attenuation of roll and pitch angles and accelerations (Crossland, 2000; 2003).

The interpretation of O as a frequency attempts to attribute to nature—in this case the actual vessel behaviour—the result of a logical analysis of uncertainty. In this paper, we subscribe to the concept that probability is not a frequency, rather a measure of uncertainty or a state of knowledge (Jaynes, 2003). That is, probability allows us to do plausible reasoning in cases where we cannot reason with certainty. We consider an alternative framework for the assessment of operability. We pose O as a hypothesis or proposition, namely a real property of the vessel, which can either be true or false and to which we seek to assign a probability of being true. The end result is the predictive probability of operability. That is, the probability that the vessel will attain the desired performance in one mission considering the envelope of likely environments and sailing conditions, namely, \( P(O|D,I) \), where a proposition D stands for data and I stands for background information. This framework aligns with current trends in Bayesian reliability and risk analysis (Singpurwalla, 2006). This paper extends the previous work in Perez (2013) by using the method to assess increase in operability due to ride control. It also incorporates a discussion on the assessment of autonomy.

2. STANDARD OPERABILITY COMPUTATION

Standard seakeeping analysis considers long-term wave distributions, namely the joint distribution of probabilities \( P(H_i,T_j) \) \( (i = 1, \ldots, r; j = 1, \ldots, s) \), where \( H_i \) and \( T_j \) are the following propositions:\footnote{A proposition is a logic statement that can either be true or false.}

\[
H_i : \{H_i \leq H_s \leq \overline{H}_i\},
\]
\[
T_j : \{L_j \leq T \leq \overline{T}_j\}.
\]
The motion spectra weighted membership function:

\[ w_{ijklm}(\omega, U, \chi, H, T) = |F_d(\omega, U, \chi)|^2 S_p(\omega, H, s, T), \]

with \( d = 1, 2, \ldots, 6 \). Note that the use of frequency response functions assumes linear ship response characteristics. This means that the effect of motion control systems used to reduce roll and pitch motion cannot be captured fully—neither adaptation of the control strategy to changes in environmental conditions, nor loss of performance due to actuator saturation is contemplated (Perez, 2005; Perez and Blanke, 2012).

The uncertainties associated with the sailing conditions is represented by the joint probability distribution of vessel speeds \( U_k \) (\( k = 1, \ldots, t \)) and wave encounter angles \( \chi_l \) (\( l = 1, \ldots, u \)). For simplicity though, the speeds and encounter angles are assumed to be independent, namely, \( P(U_k, \chi_l) = P(U_k)P(\chi_l) \). The distribution \( P(U_k) \) is dictated by the operations the vessels conduct (transit, station keeping, equipment launch and recovery, etc.). Except for particular areas of operation in the globe, the distribution \( P(\chi_l) \) is taken to be uniform in \([-\pi, \pi]\).

The motion spectra \( S_d(\omega, U, \chi, H, s, T) \) (\( d = 1, 2, \ldots, 6 \)) are used to compute ship-motion acceleration spectra and statistics (e.g. root mean square, single significant amplitude, double-significant amplitude) in the degrees of freedom of interest. These statistics are then mapped into performance indices \( R_m \) (\( m = 1, \ldots, v \)) for (example, roll angle statistics, number of propeller emergences per hour, motion sickness index, slamming) which are compared with mission required threshold values (limits) and weighted according to their importance to determine a set of operability coefficients \( W_{ijklm} \in [0, 1] \) associated with each scenario—wave height, wave period, speed, and encounter angle. It is very common to take \( W_{ijklm} \) as a weighted membership function:

\[ W_{ijklm} = k_m w(R_m), \]

where

\[ w(R_m) = \begin{cases} 1 & \text{if } R_m \in R_m, \\ 0 & \text{otherwise}, \end{cases} \]

and \( R_m \) is the set of values for which the performance is deemed satisfactory, and the coefficients \( 0 < k_m < 1 \) weight the importance of the different performance indices—note the constraint \( \sum_m k_m = 1 \). Alternatives to the \( w(R_m) \) above with a more gradual degradation as \( R_m \) approaches the boundaries of \( R_m \) have also been proposed to reduce the sensitivity of \( W_{ijklm} \) to small variations of \( R_m \) close to set boundaries—see, for example, RAN (2003).

Once the operability coefficients are computed, the figure of merit of operability is computed as follows:

\[ O = \sum_{i,j,k,l,m} W_{ijklm} P(H_i, T_j) P(U_k) P(\chi_l). \]

The coefficient \( O \) can be used a single figure of merit of a particular vessel, and the coefficients \( W_{ijklm} \) can be used to assess performance in more detail.

For the assessment of ship-ride control systems, the measure of performance is the increase in operability due to the action of the ride control system (Crossland, 2000, 2003):

\[ \Delta O = O_{st} - O_{ol}. \]

Where \( O_{st} \) and \( O_{ol} \) stand for closed loop and open loop respectively.

3. COMMENTS TO THE STANDARD APPROACH

Equation (1) mixes probabilities with weighting coefficients \( W_{ijklm} \) that are deterministic in nature. By construction, the coefficient \( O \) takes values in the range \([0, 1]\), and due to this, \( O \) is then ‘interpreted’ as a frequency or as percentage of time operable (Lloyd, 1998; NATO, 2000). One could also give (1) a decision-theoretic interpretation, where the coefficients \( W_{ijklm} \) would represent a utility and \( O \) would thus be a expected utility or risk (Lindley, 1991). To the best of the author’s knowledge, this interpretation, has not been yet been discussed in the literature, and nor will it be discussed in this paper.

Although the metric \( O \) serves the purpose of expressing performance in a cardinal scale, and when computed for different vessels, it allows one to make comparisons, the frequency interpretation is a rather far-fetched concept. The computations through (1) provide little support for such interpretation. A decision-theoretic interpretation may also be difficult to justify since no decision problem is alluded for the calculation of \( O \). One could argue, however, that there is an underlying decision problem. Indeed, the purpose of seakeeping analysis is to infer \( O \), and this used as key information for the associated with the decision problem which also requires the elucidation of the utilities of the decision maker. The latter, however, is a different, and harder, problem altogether; and therefore, it has been argued that inference should be separated from decision (Jaynes, 2003) (page 405).

Since we are dealing with uncertainty, and the end user will be using the information from the seakeeping analysis for making a decision under uncertainty, it would be, perhaps, more convenient to investigate the use of a procedure to compute \( O \) that has its foundation in probability theory. Then, the seakeeping analysis would provide the probabilities that can be used as part of a subsequent decision problem (for example, to choose one vessel over another, or to accept a design vs requiring modifications and re-assessment).

To develop this approach using probability, we propose to consider the following hypothesis:
O: {The mission prescribed performance is satisfied over the required operational conditions}, (3)
and then evaluate its probability conditioned on all available background information I and the data D from the seakeeping computations, namely, \( P(O|D, I) \).

The above departs from the standard analysis. First, we shall talk about the probability of operability. This makes a clear distinction between the operability \( O \) as a real characteristic of a ship and its probability, which is only a description of our state of knowledge, or uncertainty, about its truth or falsity. Second, with this view, \( O \) is binary, and the scale for comparison of different designs is given by the probabilities.

When we use probabilities to describe our uncertainty about a proposition based on our current state of information, Bayes’s Theorem is the tool that allows to update our knowledge in the light of new evidence. This provides unique rules for conducting inference. Any other set of rules has been found to violate a desiderata of rationality and consistency (Cox, 1946; Jaynes, 2003):

I) Degrees of plausibility are represented by real numbers,
II) Rationality: qualitative correspondence with common sense.
III) Consistency:
   IIIa) If a conclusion can be drawn in more than one way, every way must lead to the same result.
   IIIb) In doing plausible reasoning, we must take into account all information available.
   IIIc) Equivalent states of knowledge are represented by equivalent degrees of plausibility.

Starting from these desiderata, Cox (1946) and Jaynes (2003) develop probability theory as an extension to logic. Here, we will follow a Bayesian approach for computing \( O \). We formulate this approach in the following section.

4. PROBABILISTIC OPERABILITY

For a given mission or operation, we will associate to the vessel a set of performance indices related to motion \( R_m \) (\( m = 1, \ldots, v \)). Table 1 shows examples of performance indices— for details see RAN (2003) and NATO (2000).

Table 1. Example of performance indices and operability limits for transit operations. MSI - Motion Sickness Index (related to vertical acceleration). MII - Motion Induced interruptions (related to transverse acceleration as well as gravity). Note that the human related indices (accelerations, MSI, and MII) are considered at particular locations on the vessel. To each performance index \( R_m \), we associate a set \( R_m \) of satisfactory performance. Table 1 shows examples of limits that define the boundaries of the sets \( R_m \) associated with particular performance indices. We then consider events or propositions

\[
E_m = \{ R_m \in R_m \ \forall T_M \}, \quad m = 1, \ldots, v.
\] (4)

where \( T_M \) the duration of the mission or the evaluation period. The events \( E_m \) in (4) are statements about performance of each index and they can either be true or false. \( E_m \) is true when the performance index \( R_m \) takes values that in agreement with its required performance, namely, \( R_m \in R_m \) for the duration of the mission \( T_M \). The operability requires that all the measures of performance be satisfied simultaneously. For example, for \( R_1 \) in Table 1, \( R_1 = \{ R_1 : |R_1| \leq 0.2g \} \).

Then, we can consider operability as the joint event

\[
O = \bigcap_{m=1}^v E_m = E_1 \cap E_2 \cap \cdots \cap E_v.
\] (5)

Note that since the events \( E_m \) are proper propositions, the event \( O \) is also a proposition: \( O \) will true if and only if all the events \( E_m \) are true.

We can then consider time-domain data, which consists of time series of motion obtained under particular testing scenarios (simulations under specific environmental and sailing conditions). These can be simulated form in information of the wave spectra and vessel frequency response functions, or from dynamic models that incorporate the effect of motion stabilisation control (Perez, 2005). If we produce \( N \) replications (simulations) of the vessel motion response in a particular operational and sailing condition and assess the truth of the event \( O \), we will obtain a sequence of binary data:

\[
D = \{ d_1, d_2, \ldots, d_N \}, \quad d_i = \begin{cases} 1 & \text{if } O \text{ is true,} \\ 0 & \text{otherwise.} \end{cases}
\] (6)

Then, compute the probability of operability by marginalisation:

\[
P(O|D, I) = \sum_{i,j,k,l} P(O|H_i, T_j, U_k, X_l, D) \times P(H_i, T_j|I) \times P(U_k|I) \times P(X_l|I).
\] (7)

Note that expression (7) is an aggregate of different components of uncertainty:

- **Environment:** The probability distribution \( P(H_i, T_j|I) \) captures uncertainty about the weather or environmental conditions that are likely to be encountered during the mission at the required ocean area.
- **Sailing condition:** The product of probabilities \( P(U_k|I) \times P(X_l|I) \) captures the uncertainty in the sailing conditions in which the vessel is likely to conduct the mission.
- **Vessel handling:** The conditional probabilities \( P(O|H_i, T_j, U_k, X_l, D) \) capture uncertainty in the way the vessel handles particular operational conditions. This is related to vessel design, mass distribution, and motion control systems.

In the above, there is the underlying assumption here that the speed and heading are conditionally independent. This is not always true. Furthermore, there may also be a de-
pendancy on the sea state: in severe sea states, human decisions affect encounter angles and operational speeds (voluntary speed reduction). The independence assumption, however, simplifies the computations, for it would hard to determine the joint distribution \( P(H_i, T_j, U_k, \chi_j|I) \).

If we compare (7) with (1), we can see that in the probabilistic formulation (7) we have replaced the weighting coefficients in (1) by the vessel handling probabilities. In the next section, we discuss how to compute these vessel-handling probabilities.

5. PREDICTED VESSEL-HANDLING PROBABILITIES

As mentioned in the previous section, the proposed operability computation is based on time-domain data. Form the spectra of motion, we can draw realisations of time series—this assumes linear vessel response including the action to the ship motion control systems (Perez, 2005). Alternatively, we can draw realisations of wave excitation forces and simulate time-domain models obtained from excitation RAOS plus additional features, which can be non-linear, related to motion control systems (Perez and Fossen, 2011). The idea is that we can create replications of the simulations under specific conditions.

If we produce \( N \) replications of records (simulations) of vessel motion response in a particular operational condition (environment and sailing conditions), then for each replication, we can evaluate whether the event \( O \) is true or false. This will lead to a sequence of binary data (6). If the replications are independent, then the probability of obtaining a particular dataset of the form (6) is given by

\[
P(D|\theta, I_{ijkl}) = \prod_{i=1}^{N} \theta^{d_i} (1 - \theta)^{1-d_i} = \theta^R (1 - \theta)^{N-R},
\]

where the parameter \( 0 \leq \theta \leq 1 \) represents the probability of success in one trial, \( R \) is the number of successes in the \( N \) replications \( (R = \sum d_i) \), and \( I_{ijkl} \equiv \{H_i, T_j, U_k, \chi_j, I\} \) represents the information related to the particular condition being tested plus any other prior information \( I \). Expression (8) can be used as a likelihood function to infer the value of the parameter \( \theta \).

5.1 Inference

The parameter \( \theta \), assumed constant, is uncertain. We can describe this uncertainty using a prior distribution for the parameter \( p(\theta|I_{ijkl}) \). Note that within a Bayesian approach, a prior distribution for a parameter does not mean that the parameter is random. The parameter is constant, and the distribution describes our uncertainty about its value—what is distributed is the probability not constant, and the distribution describes our uncertainty mean that the parameter is random. The parameter is approach, a prior distribution for a parameter does not determine the joint distribution

\[
P(O|H_i, T_j, U_k, \chi_j, D) = \int_0^1 p(\theta|D, I_{ijkl}) \, d\theta.
\]

If we adopt a uniform distribution for the prior \( p(\theta|I_{ijkl}) \) in (9), then vessel-handling probabilities reduce to

\[
p(O|H_i, T_j, U_k, \chi_j, D) = \frac{R + 1}{N + 2}.
\]
Although the analysis above have been developed for the event $O$, it can also be carried out for each individual event $E_m$ with a simple re-definition of the data (6). This can be done to gain further insight: a scrutiny of the index-specific handling probabilities $P(E_m|H, T_j, U_k, \chi_3, D)$ can reveal what are the limiting factors that lower the overall operability.

In the above analysis, we have considered the problem of assessing the performance of each simulation in terms of binary assessments (the performance is either satisfied or not), and this led to a simple likelihood function (8). For metrics like number of propeller emergences per hour, this would require the simulation of one-hour scenarios and counting the number of events in order determine whether the performance is satisfied or not. Alternatively, one could consider a likelihood based on the Poisson distribution. This is beyond the scope of this paper.

### 6. EXAMPLE

As an example to illustrate some of the calculations, we consider a 364t navy patrol vessel (LOA - 52m, BOA - 8.6m) from Perez (2005). Figure 1 shows the hull shape. We consider a reduced operability computation with only the performance indices $R_1$ and $R_2$ indicated in Table 1, and the accelerations are evaluated at the bridge of the vessel.

![Navy patrol vessel](image_url)

**Fig. 1.** Navy patrol vessel adapted from Perez (2005).

Instead of a total operability, we consider the operability for a particular wave height for the range $H = [2, 3]$. The conditional probabilities of the zero-crossing periods based on Southern Ocean data (Area 100) are detailed in Table 2.

| $T$ [s] | 5-6 | 6-7 | 7-8 | 8-9 |
|---------|-----|-----|-----|-----|
| $P(T|H = [2, 3])$ | 0.0041 | 0.0816 | 0.2857 | 0.3469 |

| $T$ [s] | 5-6 | 6-7 | 7-8 | 8-9 |
|---------|-----|-----|-----|-----|
| $P(T|H = [2, 3])$ | 0.0040 | 0.0653 | 0.0122 | 0.0041 |

**Table 2.** Conditional distribution of wave periods for a given wave height in the range of 4 to 5m for the southern Ocean (Area 100).

We consider a single vessel speed $U = 10kt$ and three encounter angles: quartering (45deg), beam (90deg), and bow (135deg). The encounter angles are assumed to have uniform distribution—they are equally likely to be encountered during the mission.

Figure 2 shows the outcomes of 100 simulations of time series of 30 minutes for wave periods in the range 10-11s and bow seas. The top plot shows the binary data (6) and the bottom plot shows the corresponding posterior density $P(\theta|D, I_{ijkl})$ computed from (9). In this case, the main limiting factor is roll-induced lateral acceleration, which is a consequence of the encounter frequency being close to the roll natural frequency. The corresponding predicted vessel-handling probability (14) is 0.647. Figure 3 shows the results corresponding to wave periods in the range 6-7s. In this case, the outcomes in which the performance is not satisfied is due to vertical accelerations induced by a combination of heave and pitch. The corresponding predicted vessel-handling probability (14) is 0.941. The operability for the given wave height condition is

$$P(O|D, H, U, I) = \sum_{j=1}^{8} \sum_{l=1}^{3} P(O|H, T_j, U, \chi_3, D)$$

If we repeat the analysis with the vessel with a gyro-stabiliser (Donaire and Perez, 2013), we obtain that the $P(O|D, H, U, I) = 0.97$.

![Outcomes of O](image_url)

**Fig. 2.** Outcomes of $O$ for 100 scenarios for wave heights in the range 2-3m, wave zero-crossing period of 10-11s, speed of 10kt, and bow seas. The top plot shows the outcomes $d_i$ and the bottom plot shows the posterior density $P(\theta|D, I_{ijkl})$.

### 7. ASSESSMENT OF AUTONOMY

As developments in autonomous systems progress, there will soon be the need to test and certify increasing levels of autonomy with a capacity of not only motion control but mission re-planning and abortion. The framework we have proposed above fits in well with the testing of autonomy with minor modifications. The performance indices, in this case, can be related to attributes of safety as well as performance such as remaining outside navigation zones, early detection of obstacles and potential collisions, appropriate re-planning of the missions, etc. The operational conditions can also include aspects of complexity of operational space, and also potential failure modes in sensors and actuators. The assessment can be done in simulation, but also with hardware-in-the-loop testing. This type of assessment and analysis can be used for certification and...
The modified operability related to autonomy becomes
\[ P(O|D, I) = \sum_{i,j} P(O|W_i, F_j, D)P(W_i|I)P(F_j|I), \]  \hspace{1cm} (15)

The distributions \( P(W_i|I) \) and \( P(F_j|I) \) capture uncertainty about the operational environment, which includes weather scenarios \( W_i \) and faults \( F_j \) under which the system is to operate. The distribution \( P(O|W_i, F_j, D) \) evaluates the quality of autonomous decision making of the unmanned system under a particular scenario given by the combination \( W_j, F_k \). The latter encompasses aspects of robustness and performance of the vehicle control system, fault detection and diagnosis system, and on-line decisions about reconfiguration of the control system and mission re-planning and trajectory planning. In this case, \( P(O|D, I) \) captures the uncertainty associated with the decision problem of certifying and or insuring a system for particular operations.

8. CONCLUSION

In this paper, we re-formulate the traditional procedure for computing ship seakeeping operability by using a full probabilistic framework. The proposed approach considers operability as a hypothesis that a vessel will attain the desired performance in one mission considering the envelope of likely operational conditions. We then use the Bayesian framework to evaluate the probability of operability. We present an example of operability calculation related to a navy patrol boat and show how the use of a ride-control system increases the probability of operability. Finally, we discuss how the framework can be adapted for the case of assessment of autonomy in unmanned vessels.

REFERENCES

Cox, R.T. (1946). Probability, frequency, and reasonable expectation. American Journal of Physics, 14(1), 1–11.

Crossland, P. (2000). The effect of roll stabilization controllers on warship operational performance. In 5th IFAC Conference on Manoeuvring and Control of Marine Craft MCMC’02, 31–37.

Crossland, P. (2003). The effect of roll stabilization controllers on warship operational performance. Control Engineering Practice, 11, 423–431.

Donaire, A. and Perez, T. (2013). Energy-based nonlinear control of ship roll gyro-stabiliser with precession angle constraints. In Proceedings of the IFAC Conference on Control Applications in Marine Systems. Osaka, Japan.

Geisser, S. (1984). On prior distributions for binary trials. The American Statistician, 38(4), 244–247.

Gregory, P. (2005). Bayesian Logical Data Analysis. Cambridge University Press.

Haverre, S. and Moun, T. (1985). Probabilistic Offshore Mechanics, chapter On some uncertainties related to short term stochastic modelling of ocean waves. Progress in Engineering Science. CML.

Jaynes, E. (2003). Probability Theory, The Logic of Science. Cambridge University Press.

Jeffreys, H. (1939). Theory of Probability. Clarendon Press, Oxford, later editions, 1948, 1961, 1967, 1988.

Jeffreys, H. (1973). Scientific Inference. Cambridge University Press.

Lindley, D.V. (1991). Making Decisions. Wiley, 2nd edition.

Lloyd, A. (1998). Seakeeping: Ship Behaviour in Rough Weather. A.R.J.M. Lloyd, 26 Spithead Av, Gosport, Hampshire, UK.

NATO (2000). Standardization Agreement: common procedures for seakeeping in the ship design process (STANAG) 3rd ed N0.4154. North Atlantic Treaty Organization (NATO), Military Agency for Standardization (MAS).

Ochi, M. (1998). Ocean Waves: The Stochastic Approach. Ocean Technology Series. Cambridge University Press.

Perez, T. (2005). Ship Motion Control. Advances in Industrial Control. Springer-Verlag, London.

Perez, T. (2013). A Bayesian approach to seakeeping operability computations. In Proc. of Pacific 2013 International Maritime Conference, Sydney, Australia.

Perez, T. and Blanke, M. (2012). Ship roll damping control. Annual Reviews in Contrlo, 36(1), 1367–5788.

Perez, T. and Fossen, T. (2011). Practical aspects of frequency-domain identification of dynamic models of marine structures from hydrodynamic data. Ocean Engineering, 38(2), 426–435.

Perez, T., Williams, B., and de Lamberterie, P. (2012). Evaluation of robust autonomy and implications on UAS certification and design. In 28th International Congress of the Aeronautical Sciences. Brisbane, Australia.

RAN, R.A.N. (2003). Standard materiel requirements for RAN ships and submarines: Part 6 seakeeping. Technical Report A016464 Revision 1, Naval Platform System Engineering Directorate, Department of Defence, Royal Australian Navy, Unclassified.

Singpurwalla, N.D. (2006). Reliability and Risk - A Bayesian Perspective. Wiley Series in Probability and Statistics. John Willey & Sons, UK.