Analysis of Windows of Opportunity for Weather-Sensitive Operations

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Summary

This paper presents an approach to the statistical analysis of weather windows of opportunity, which are defined as the time span over which the stringent, multiparametric conditions required by weather-sensitive marine operations (such as heavy lift, topside float over, and pipeline tie in) are met. For this paper, the topside float over has been used as a case study and application of the statistical analysis.

The basic data for the analysis are the numerically generated long-time-series wind, wave, and sea currents, which are becoming increasingly available from weather-forecasting models, global reanalysis studies, and project-specific metocean assessment. These long time series allow identification of climatically significant weather windows at the seasonal, and often at the monthly, time scale.

Appropriate statistical distributions to fit the weather windows are required to interpolate within and extrapolate from window durations, smooth the sample data, and obtain objective assessment of weather-window statistics. For this task, two possible distributions are proposed—the Johnson set of transformations (Johnson 1949) and the Kappa distribution (Hosking 1994)—that, although well-documented in the statistical literature, have seldom, if ever, been applied in offshore analysis. Fits on sample data are performed with the *L*-moment method (Hosking 1990, 1996, 2000) for the Kappa distribution and with both moment (Draper 1952; Hill et al. 1976) and quantile (Wheeler 1980) methods for the Johnson distribution.

The entire procedure (definition of limit conditions, identification of weather windows, and statistical analysis of weather windows) is exemplified with reference to a hypothetical float-over operation in the Andaman Sea (Myanmar). The simulation carried out indicates that the use of statistical distributions can enhance the reliability of the weather-window analysis significantly because of smoother description of weather-window durations, improved interpolation and extrapolation capabilities, and higher discriminating power of alternative design solutions.

Both the Johnson distribution and the Kappa distribution provide an overall good performance in fitting the sample data, either when subjectively assessed by visual inspection or in terms of the objective analyses of the resulting mean-square errors; hence, they are suggested as promising candidates for routine analysis of weather windows.

Introduction

Weather-sensitive marine operations, such as heavy lift, topside float over, and pipeline tie in, require stringent limits on metocean conditions, lasting for periods ranging from some hours to a few days. The limit conditions are usually defined by a multiparametric combination of wave, wind, and currents.

In offshore activities, the statistical analysis of the weather windows is relevant to support facility layout design, selection of the optimal season for site activities, and for the definition of the technical approach that is most suitable for minimizing overall operational costs on the basis of the appropriate balance of equipment and expected downtime.

Traditionally, the statistics of weather windows were based on persistence analysis, with consideration of a single parameter and severe limitations because of the short and usually discontinuous time series available, so that a large part of the effort was devoted to the extension of the original time series to obtain statistically reliable estimates. Both the methodology of persistence analysis and the techniques for time-series extension are summarized in Barltrop (1998).

More recently, the availability of long (10 to 50 years), numerically simulated time series from public institutions [e.g., the National Oceanic and Atmospheric Administration (NOAA) Environmental Modeling Center (2014)] and private enterprise [e.g., Ocean Weather Inc. (2001)] has allowed a more-realistic approach to analysis of weather windows, removing the limitations to the single variable of persistence analysis [see, for example, Fugro GEOS (2011) and Fraunhofer IWES (2014)].

In most cases, the analysis relies on a counting process on the time series, with linear interpolation to estimate quantiles of weather windows. However, this leads to some difficulties related to the sample size (especially for analysis at the monthly level) and the finite time resolution of the original time series, resulting in ragged statistical estimates and limited discrimination capabilities among alternative design choices.

The fit of the weather windows, with appropriate statistical distributions, provides a smoother description of the sample data and allows an objective assessment of their statistical properties, thus removing or at least reducing these difficulties, but offshore literature does not show significant applications of this approach [an example to the contrary, with the use of the Weibull distribution, is in Rademakers and Braam (2002)]. In this paper, we propose two distributions—the Johnson (1949) set of transformations and the Kappa distribution (Hosking 1994)—and we provide preliminary analysis of performance. Both distributions are quite popular in the statistical literature because of their flexibility in the description of data of unknown parent population; therefore, they appear well-suited to fit the distribution of weather windows, for which (and to our knowledge) no a priori criteria can be invoked about the shape of the probability function. The distributions share the ability to mimic the shape of both bounded and unbounded distributions, to match the lower moments of any realizable statistical sample, and to allow a relatively easy computation of quantiles. On the other hand, both have four parameters, thus posing some mathematical and numerical problems in the fit of sample data,

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		Hydraulic System				Traditional Ballasting			
		Spectral Peak Period T_p (seconds)							
	Sea Direction	7	10	13	16	7	10	13	16
Limit H_s Value for Float Over (m)	Head Seas	1.50	0.99	0.99	1.03	1.50	0.85	0.99	1.03
	Head/Quartering Seas	1.39	0.96	1.05	1.01	1.39	0.90	0.83	0.67
	Quartering Seas	1.16	0.95	0.88	0.56	1.16	0.91	0.55	0.52
	Beam Seas	0.69	0.57	0.38	0.35	0.67	0.51	0.31	0.32

TABLE 1—LIMIT SEA-STATE CONDITIONS FOR FLOAT-OVER OPERATION

which are, however, greatly eased by the large amount of literature available.

In statistical literature, the Johnson (1949) distribution is documented in such different fields as epidemiology and bioinformatics, forestry and agriculture, hydrology and meteorology (Georgiadi 1993; Fang and Tung 1996), financial and portfolio analysis, and input modeling for the simulation of industrial production. The Kappa distribution (Hosking 1994) is quite popular among hydrologists for the simulation of rainfall and, generally, of storm events [see Parida (1999), Park and Jung (2002), and Asquith et al. (2006)], and is documented for analysis of wind data and extreme flood. However, they appear to be scarcely (if ever) used in ocean engineering; therefore, a brief description of their main properties is given in Appendix A and Appendix B, respectively.

Typical weather-sensitive marine operations, such as float over, tie ins, lifting, and jacket launch, share the common feature of being affected by multiple weather parameters, although with different sensitivity—wind speed is of paramount importance in lifting operations and comparatively unimportant in tie ins; currents are relevant for precision installation by dynamic-positioning vessels and much less so for float-over operations. The analysis of window of opportunity provides a common approach to these situations because an almost arbitrary number of parameters can be included in the definition of operational conditions. In this paper, the technique of analysis of windows of opportunity and the application of Johnson and Kappa distributions are exemplified with reference to a typical float-over operation. Metocean constraints and site conditions are described briefly in the following two sections, with subsequent sections on the identification and statistical analysis of the resulting weather windows.

In some instances, the limit conditions are more easily defined in terms of vessel response than of weather conditions (e.g., acceleration at crane tip, roll angle of barge during lifting operations). Although not explored in this paper, it is noted that this can be accounted for easily in the analysis of windows of opportunity by including the constraints in the definition of limit conditions. As an example, vessel response amplitude operator (RAO) can be used to transform a wave time series into displacements and accelerations, which in turn can be used as parameters in the assessment of operational windows once suitable limits are defined.

Metocean Constraints in Float-Over Operations

In a float-over operation, a barge carries the topside of an offshore platform into the frame of a preinstalled jacket and lowers it onto the jacket legs. Typical dimensions of the topside are 50×50 m, at weights in the range of 10,000 to 15,000 tons, with an upward escalation of weights for currently planned topsides in the range of 15,000 to 20,000 tons.

The main phases of float-over operations and the resulting constraints in the environmental loads are

- Entry phase (i.e., the towing of the barge into the jacket frame), when strict control on lateral movements is required to avoid overstress on fenders and potential damage to platform legs and to the barge hull
- Mating phase, when the critical aspect is avoiding unbalance in the weight distribution during the load transfer from barge to platform legs
- Exit phase, when both lateral contacts of the barge on the jacket and freeboard with respect to topside are critical items in the overall planning of the operation

Critical design decisions in planning the float-over operation are

- The entry/exit heading of the barge, which should be addressed in the early phase of platform design and overall field layout, with the aim to minimize the impact of quartering/beam seas during operation
- The design of fenders and mooring lines, the possible use of hawser lines to limit barge response to sea conditions, and the stress level in the interaction of barge and platform
- The adoption of a leg-mating unit (LMU) to smooth the load transfer from barge to jacket, thus increasing the allowed operational limits for the installation
- The selection of the topside-lowering system (passive/active ballasting, mechanical/hydraulic lowering devices), the increased technical complexities and associated costs of which could be balanced by the higher operational limits and shorter duration of the operation

Numerical simulations of the different scenarios allow for the definition of limit conditions for each possible solution. The analysis of resulting weather windows provides the basic elements to select the solutions, allowing for safe operation at the overall lower cost.

Basic Data for Analysis of Windows of Opportunity

A sample case of a fictitious float-over operation in the Andaman Sea is considered to illustrate the statistical analysis of weather windows of opportunity.

- Limit conditions for float-over options: Two possible options are considered for the mating phase—standard ballasting, with an LMU to smooth the load transfer and mechanical lowering with a hydraulic system. **Table 1** summarizes the resulting set of limit sea-state conditions, as obtained from naval numerical simulations.
- Metocean conditions: the north Andaman Sea **(Fig. 1)** is characterized by a persistent and usually dominant southwest (SW) swell (with peak period T_p of 12 to 14 seconds) that is enhanced in the summer months by the SW monsoonal winds. In winter, the reverse of the monsoonal-wind pattern from SW to northeast (NE) and the slack of the SW seas in the south Indian Ocean summer result in a more complex sea condition, with local wind waves flowing northwest (NW)/NE (with T_p of 6 to 8 seconds), superimposing and occasionally dominating the SW swell.

The analysis of the weather windows meeting the constraints of Table 1 is based on the NOAA data set (NOAA Environmental Modeling Center 2014), consisting of global 3-hourly wind and waves, with a resolution of 1.25° longitude ×1° latitude for the period spanning February 1997 to December 2010.

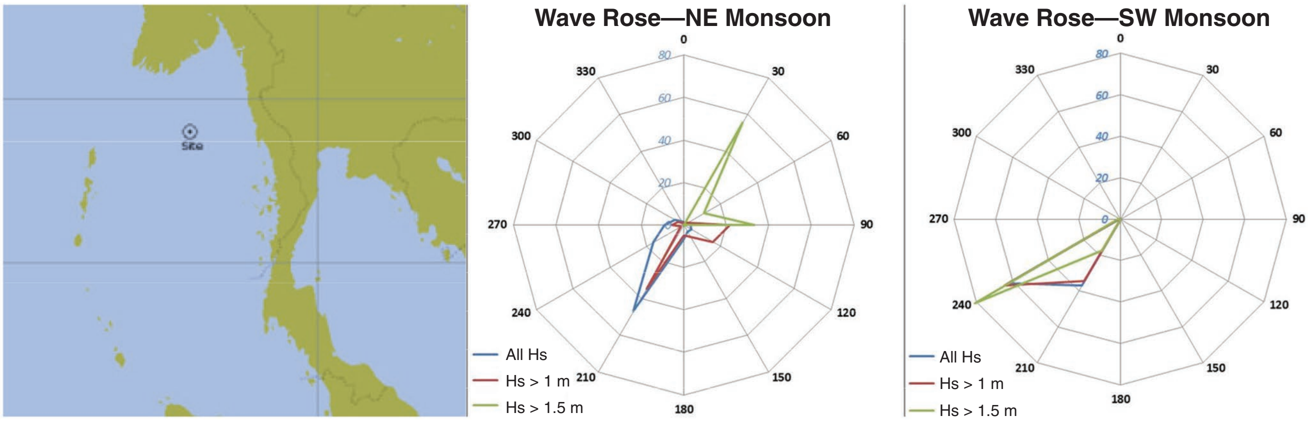

Fig. 1—Andaman Sea: Seasonal wave rise and distribution of peak period.

Statistical Analysis of Weather Windows of Opportunity

The statistical analysis of the weather windows should aim to an unequivocal identification of the most suitable period for the site operation and of the most appropriate operation assembly on the basis of a selected or imposed period of operation. Relevant statistics are the average duration of weather windows, which should exceed the time necessary to complete the operation; the expected number of weather windows because weather windows of opportunity that are widely spaced in time can result in an unacceptable long wait on weather (WoW) at site; and the percentiles of weather windows, which provide a measure of how fault tolerant site conditions could be (i.e., the probability of having suitable conditions for contingencies that extend the planned duration of the operation). To illustrate the possible intuition from the statistical analysis, a sample case (chosen from the 60 samples that were run) containing the months September, October, and December has been selected. In this sample case, the conditions during the SW monsoon are too rough for operation. Hence, suitable weather windows have been explored for September (end of the rough season), October (transition from SW to NE monsoon), and December (NE monsoonal conditions).

Table 2 clearly indicates the improvements of site conditions progressing toward the NE monsoon; the slightly higher average duration of operational windows in October is more than compensated by the higher number of windows in December, with an overall increase of expected operational time (70 vs. 41%). Conversely, in September, operation should cope with short windows (on average less than 24 hours) and limited overall operational time (approximately 11% of a month's duration).

The selection among different operational solutions requires some refinement of the statistical analysis because less stringent metocean constraints should be balanced against increased cost of equipment. **Table 3** compares the statistics of the weather windows for the two scenarios (standard ballasting vs. hydraulic lowering for the mating phase) for the metocean conditions in December, while **Table 4** illustrates the statistics for the month of January should there be a need for a delay in fabrication or transportation of the float-over operation.

In the table, P ($\geq n\ h$) indicates the probability that, once a window occurs, it will last more than the threshold duration. All other statistics are only based on events longer than the threshold duration (e.g., WoW includes both nonoperational periods and windows lasting less than the threshold). Hence, in this example, the adoption of a hydraulic lowering system will increase the average duration of operational windows slightly and reduce the WoW time. (Another obvious advantage that is not outlined in the table is the higher probability of obtaining operational windows because of faster operation, thus requiring a shorter operational period.)

Statistical Fit of Weather Windows of Opportunity

In this preliminary application, the goal in the use of the of the Johnson and Kappa distributions was to verify their flexibility to fit all possible outcomes of the weather-windows analysis, with some feedback on their relative performance. A data set of 60 samples was generated with the limit conditions of Table 1 on a monthly, seasonal, and yearly basis, considering both windows of opportunity and WoW windows (i.e., time periods with nonoperational conditions).

The moment (Hill et al. 1976) and quantile (Wheeler 1980) methods have been used to fit the Johnson distributions, with automatic selection of the most appropriate Johnson curve (see Ap-

TABLE 2—ANDAMAN SEA: FLOAT-OVER OPERATION WITH TRADITIONAL BALLASTING—STATISTICS OF OPERATIONAL WINDOWS

Periods	Number of Events	Fraction Op. Time (%)	Ave. Dur.	St. Dev.	Percentiles of the Duration of Operational Windows (days) 50	75	80	85	90	95	99	99.9	99.99
September	3.38	11.22	0.99	0.92	0.63	1.44	1.63	2.01	2.75	3.09	3.7	3.86	3.38
October	8.46	41.69	1.53	1.59	1.00	2	2.25	3.13	3.38	4.43	7.97	8.22	8.46
December	11.77	69.79	1.84	2.27	0.88	2.59	2.93	4.14	4.75	6.79	11.19	13.94	11.77
January	10.23	71.96	2.18	2.41	1.38	3.28	4.00	4.67	5.24	7.68	12.80	19.73	20.42

Notes:
Op. = Operation
Ave. Dur. = Average Duration
St. Dev. = Standard Deviation

TABLE 3—ANDAMAN SEA: OPERATIONAL WINDOWS FOR FLOAT-OVER OPERATION—COMPARISON OF TRADITIONAL BALLASTING AND HYDRAULIC LOWERING (DECEMBER)

	Hydraulic Lowering					Traditional Ballasting				
Op. Duration Threshold	$P(\geq n\ h)$ (%)	Number of Windows	Average Duration (days)	Op. Time (%)	Average WoW (days)	$P(\geq n\ h)$ (%)	Number of Windows	Average Duration (days)	Op. Time (%)	Average WoW (days)
6 hours	91.18	6.2	4.2	83.5	2.3	79.55	2.7	1.22	69.26	9.7
12 hours	73.53	5.0	5.1	82.0	3.1	69.28	8.2	2.54	66.94	3.4
18 hours	60.78	4.1	6.0	80.2	4.1	54.25	6.4	3.10	63.80	4.8
24 hours	51.96	3.5	6.9	78.4	5.2	47.71	5.6	3.41	61.76	5.8
36 hours	46.08	3.1	7.6	76.6	6.4	39.22	4.6	3.91	58.22	7.7
48 hours	43.14	2.9	8.0	75.4	7.1	29.41	3.5	4.64	51.83	11.8

TABLE 4—ANDAMAN SEA: OPERATIONAL WINDOWS FOR FLOAT-OVER OPERATION—COMPARISON OF TRADITIONAL BALLASTING AND HYDRAULIC LOWERING (JANUARY)

	Hydraulic Lowering					Traditional Ballasting				
Op. Duration Threshold	$P(\geq n\ h)$ (%)	Number of Windows	Average Duration (days)	Op. Time (%)	Average WoW (days)	$P(\geq n\ h)$ (%)	Number of Windows	Average Duration (days)	Op. Time (%)	Average WoW (days)
6 hours	91.14	4.8	5.7	88.40	0.7	87.27	7.4	3.0	71.56	1.2
12 hours	84.81	4.5	6.1	88.03	0.8	74.55	6.3	3.4	70.10	1.5
18 hours	70.89	3.7	7.2	86.51	1.1	60.00	5.1	4.1	67.93	1.9
24 hours	65.82	3.5	7.6	85.67	1.3	52.73	4.5	4.6	66.22	2.3
36 hours	58.23	3.1	8.4	83.87	1.6	39.09	3.3	5.8	62.07	3.6
48 hours	50.63	2.7	9.4	81.45	2.1	27.27	2.3	7.8	57.51	5.7

pendix A). In almost all cases, this has resulted in the bounded S_B transformation. The L-moment fitting method (Hosking 2000) has been adopted for the Kappa distribution.

Fig. 2 shows an example of fit of weather-windows data with the Johnson distribution for the case of a float-over operation with traditional ballasting and hydraulic lowering. A similar fit (for a different simulation) that uses the Kappa distribution is shown in **Fig. 3.** These sample figures can be used to illustrate a number of features of the proposed methodology that we consider to be significant improvements with respect to a counting process on time series, and they can be used to justify the extra effort of applying a best-fit function in the evaluation of weather windows.

First, the overall fit is usually quite good, notwithstanding the variability of shapes shown by sample data. An attempt at an objective assessment of the fitting performance for both distributions is given later in this paper. Experimenting with the Johnson distribution has shown that adopting alternative estimating methodologies usually solves even cases of unsatisfactory fit. For this reason, further work is in progress to implement additional estimators for both Kappa and Johnson distributions.

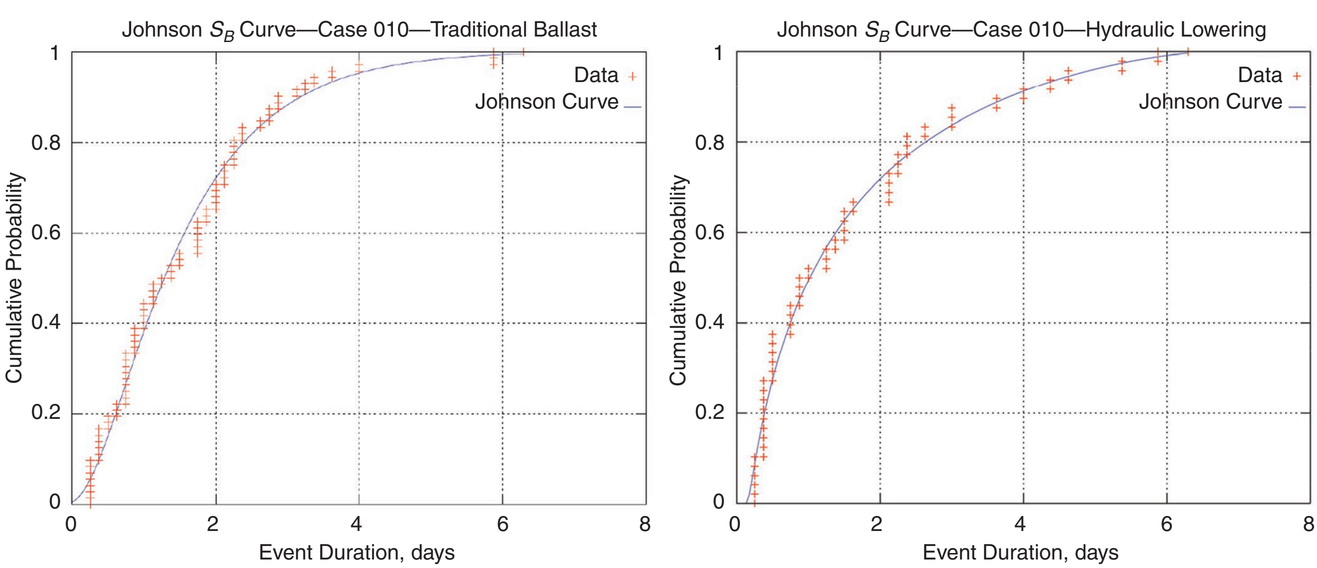

Fig. 2—Johnson S_B distribution: Best fit of windows of opportunity.

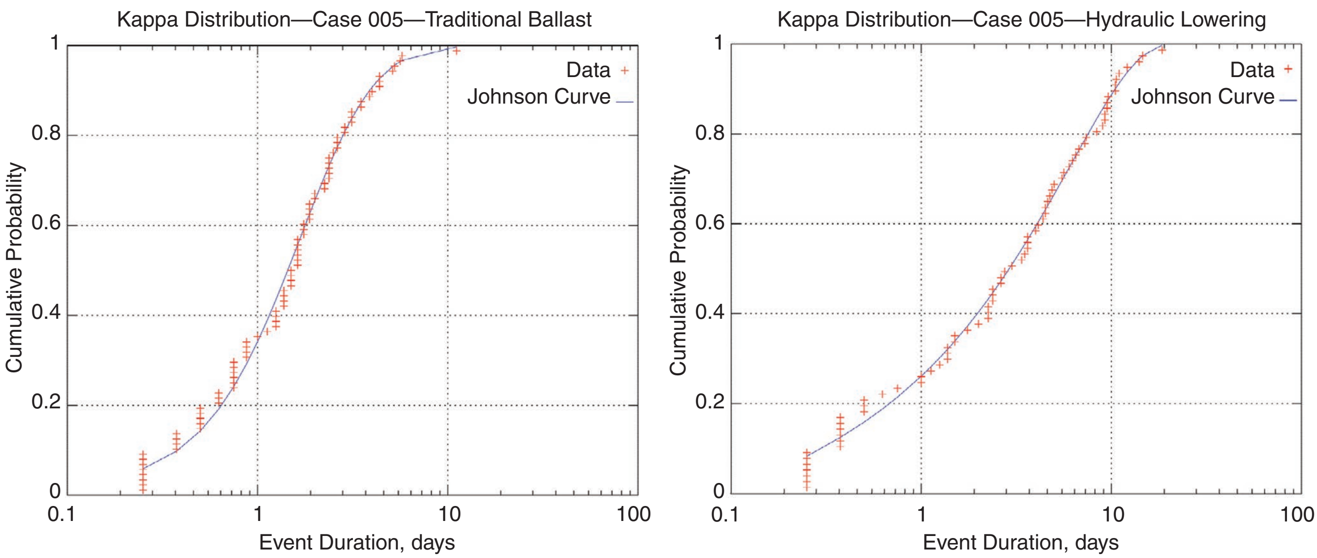

Fig. 3—Kappa distribution: Best fit of windows of opportunity.

The smooth description of the weather-windows duration obtained from the theoretical distributions allows objective assessment even for conditions described poorly by sample data (see the gap between 4 and 6 days in Fig. 2, left) and in which linear interpolation would be quite unreliable given the clearly nonlinear shape shown by the sample. This problem is clearly exacerbated when analysis is performed on short time periods (e.g., comparing two possible operational months) with reduced sample sizes, which can limit severely the discriminating capability (i.e., the ability to identify the better conditions) of an approach based on sample counting/linear interpolation. For example, in this case, the linear-interpolation method will yield a probability of 0.026 of having windows lasting more than 5 days (interpolation between the observed durations of 4 and 5.875 days), while the Johnson S_B distribution will return a probability of 0.0167 (i.e., approximately one-half the linear interpolation), so that the former can result in an overconfident approach, with possible cost and safety hazards for the project.

A related issue is caused by the stepwise nature of the sample windows with possible large uncertainties in the assessment of the probability of weather windows. In the right panel of Fig. 2, the 9-hour weather windows span the probability range of 10 to 27% in the sample data, and, consequently, the 12-hour window spans the range of 27 to 37%. As shown by the Johnson fit, this can possibly underestimate the probability of windows lasting more than 9 hours and almost certainly overestimate the probability of windows lasting more than 12 hours. It should be noted that the impact of this uncertainty is twofold. On one side, it affects the planning reliability, and on the other side, it can lead to withdrawal of a potentially advantageous design solution that cannot be justified only because of the limited discriminating power of the weather-windows analysis. Again, from the figure, reducing the duration of operation from 18 to 12 hours extends the probability of operational windows by 13% according to the Johnson fit, while it is only approximately 5.5% from sample data (or worse, any number between 0 and 16% can be claimed on sample data).

Hence, the smooth description of sample data, the improved interpolation/extrapolation capability, and the higher discrimination power are all reasons to recommend the use of suitable and suitably fitted distributions in the analysis of weather windows for engineering purposes. The testing performed within this work has shown that both the Johnson and the Kappa distributions have the

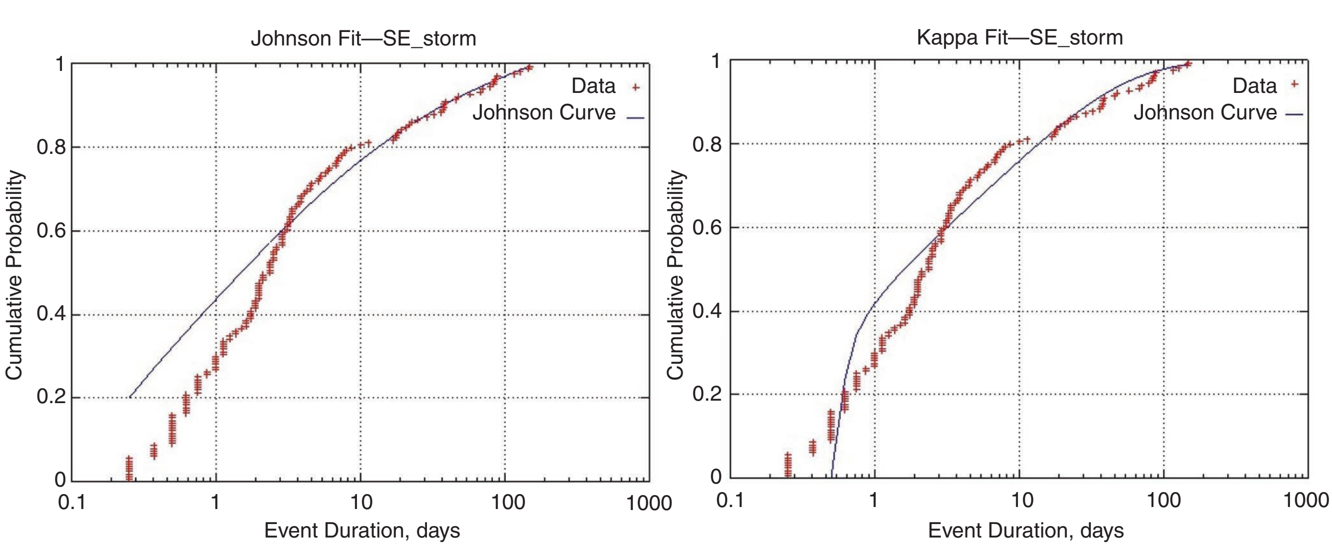

Fig. 4—Johnson and Kappa bad fit.

TABLE 5—STATISTICS OF DISTRIBUTION FIT ON SAMPLE DATA

	Installation Method	Johnson: Moment Fit		Johnson: Quantile Fit		Kappa: *L*-Moment Fit	
		$\mu(x_{m.s.e.})$	$\sigma(x_{m.s.e.})$	$\mu(x_{m.s.e.})$	$\sigma(x_{m.s.e.})$	$\mu(x_{m.s.e.})$	$\sigma(x_{m.s.e.})$
Before Removal of Outliers	Hydraulic lowering	1.155	2.052	0.435	1.021	0.318	0.687
	Traditional ballasting	0.560	1.161	0.544	0.643	0.216	0.288
After Removal of Outliers	Hydraulic lowering	0.392	0.388	0.252	0.205	0.204	0.289
	Traditional ballasting	0.371	0.532	0.544	0.653	0.216	0.289

flexibility required to fit sample weather-window durations, and are therefore promising candidates for this task; however, a cautionary note is required. As shown in the example of **Fig. 4,** we have encountered cases in which neither of the two distributions is able to fit the sample data[1] properly. In most cases, this is because of the distribution fitting only one extreme of the data (in the examples, the upper tail). While this can be accepted operationally in view of the sought after results (i.e., in these examples, if only durations longer than 10 days are relevant), this clearly indicates that the use of best-fitting Johnson and Kappa distributions is not fault proof and careful analysis of the results (coupled with the goodness-of-fit statistical tests) is required before committing them to design choices.

An objective assessment of the performance of the distributions has been attempted considering the mean-square deviation of the variate (see Eq. 1). Preliminary visual checks on the statistical fit are also used. Moreover, although given only cursory consideration in this paper, statistical tests (χ^2, Q–Q, Kolmogorov-Smirnov) are implemented in the software used for best fit and to check the goodness of fit.

$$x_{m.s.e.} = \sqrt{\frac{\sum_{i=1}^{N}\left(x_{i,\text{theo}} - x_{i,\text{sample}}\right)^2}{N}}, \quad (1)$$

where subscripts theo and sample refer to distribution estimate and sample, respectively.

Table 5 shows the results in terms of average values μ and standard deviation σ of $x_{m.s.e.}$ for the entire sample and for the reduced sample obtained after removing possible outliers. Note that data more than 3σ apart from average are treated as outliers because of the empirical rule that states that all values lie within three standard deviations of a normal distribution.

From this preliminary and somewhat limited exercise, some conclusions can be derived:

- Documented estimators for Johnson and Kappa distributions are statistically robust—out of 60 samples, failure to fit occurred in only two cases for the Johnson distribution (quantile fit) and in only three cases for the Kappa distribution.
- Both visual inspection and statistical measures indicate, on average, a good performance for both distributions, but, as suggested by the rather large standard deviation in Table 4, this results from a combination of excellent and poor performances rather than from an overall acceptable performance. On average, the Kappa distribution provides a better fit.
- The removal of the potential outliers (Table 5) both improves and makes closer the performances of the two distributions, with the Kappa distribution maintaining a lead.

Overall, the results obtained are promising and both distributions appear to be useful tools in the analysis of weather windows of opportunity, although careful inspection of fit is required before drawing conclusions—analysis is not automatic and fault proof.

Conclusion

The availability of long, numerical time series of wind, wave, and sea currents allows rather sophisticated statistical analysis for weather-sensitive marine operations with multiparametric constraints and with potentially significant optimization in the planning of site activities and in the selection of engineering solutions, leading to reduced overall cost and improved safety of the operation.

In this context, flexible statistical distributions, such as the Johnson (1949) and Kappa (Hosking 1994) distributions, can be useful tools for the objective analysis of weather windows and for the comparison of different engineering approaches. The examples provided in the paper indicate how the smooth description of sample data, the improved interpolation/extrapolation capability, and the increased discriminating power provided by statistical distribution can enhance the analysis of weather windows significantly with respect to straightforward inspection of sample data, thus justifying the extra effort involved in the statistical fit of the data themselves. Although still quite preliminary, the set of tests carried out with the Johnson and Kappa distributions indicates an overall good performance in the fit of the sample weather windows, in terms of either visual verification of the fit or the objective assessment of mean-square deviation from sample data; therefore, both distributions are appealing candidates in the routine analysis of weather windows of opportunity. Tests with the Johnson distribution show that their performance and robustness can be improved by the availability of alternative fitting methods. For this reason, further work is in progress to implement additional estimators—the least-square error for the Johnson distribution and the maximum likelihood for the Kappa distribution.

The fitting process is not fault proof, and careful selection of the distribution and fit method (as well as subjective and objective verification of the goodness of fit on sample data) is necessary to obtain meaningful statistical results and commit them to design choices.

In addition to the technicalities of the fitting process (fitting methods, objective assessment of the goodness of fit) outlined in the preceding paragraphs, an interesting extension of the approach is the inclusion of ship response to the set of constraints. Currently, the set of limit conditions is defined by naval numerical simulation of the overall system (e.g., barge, topside, jacket in float-over operation) for a forcibly limited set of cases. In some instances, the

[1]The statistical fit usually improves with sample size, but in this, there exists a conflict between accuracy and resolution. Extending the period over which the weather windows are evaluated would improve the accuracy because more windows would be identified in the time series; however, it could be misleading to evaluate the occurrence and duration of weather windows in a specific month of the season in which the operation is planned. One of the aims of the paper is to show that use of appropriate statistical distributions to analyze weather windows can overcome this in part, allowing a robust estimate from a sample of limited size.

use of vessel RAO would allow an acceptable description of vessel response, making it reasonably simple to obtain a time series of displacement and acceleration to parallel that of weather and sea condition. The flexibility inherent to the analysis of weather windows of opportunity would allow their incorporation into the definition of operational windows as an additional set of constraints with properly defined acceptable ranges.

Recommendations and Path Forward

The concept of weather windows of opportunity—incorporating in the same analysis multiparametric weather constraints and possibly even ship response—and the use of a suitable statistical method for their analysis allow for a much more detailed exploration of operational periods with respect to traditional persistence analysis. This contributed to a more informed decision about operation season, suitable vessels, appropriate methodologies, and tools to meet the safety target and economic constraints of weather-sensitive marine operations. However, in itself, this remains a small part of the overall work involved in the planning of complex marine operations. Large efforts, careful analysis, and, in most cases, subjective informed decisions are required to explore vessel availability, procurement issues, financial and commercial aspects, and legal bonds with clients and stakeholders. Considering the cost of a marine spread alone, a typical float-over operation is rated on the order of USD 500,000/D, and the stakes at issue in cases of delay or failure can be much higher than this.

Hence, considerable benefits could be expected from models that can aid the objective assessment of alternatives and the optimization of the overall approach. In this respect, linear optimization models (LOMs) provide a reasonably simple and effective tool (Hurlbert 2012; Ye and Luenberger 2008). LOMs are based on minimization of a linear (or linearized) multiparametric function that is subject to constraints. As an example in the present context, LOMs can be used to search the minimum cost, subject to constraints deriving from commercial agreements, scope of work, liquidity damage, and cost of the marine spread. Such a model can also be used to incorporate alternatives and associated risks, such as those arising from procurement issues (e.g., the length of time required to receive an item and the consequence if delivery is delayed) or vessel availability (e.g., mobilization cost and length of time required to obtain a performing vessel). Hence, an interesting extension of weather-window analysis would be the incorporation of weather windows into decision aid tools, allowing for objective exploration of alternatives in project design and operational planning to achieve the most effective solution in terms of cost, safety, and created value.

Nomenclature

H_s = significant wave height, m
N = number of data
T_p = peak period, seconds
μ = mean value of the sample
σ = standard deviation of the sample

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Appendix A: The Johnson Set of Transformations

The Johnson (1949) distribution consists of a set of four transformations between a continuous random variable x of unknown distribution and the standardized normal variate z. Formally, the probability-density function is

$$f_X(x)=\frac{\delta}{\lambda\sqrt{2\pi}}\,g'\left(\frac{x-\xi}{\lambda}\right)e^{-\frac{1}{2}\left[\gamma+\delta\cdot g\left(\frac{x-\xi}{\lambda}\right)\right]}, \qquad \text{(A-1)}$$

the cumulative distribution is

$$F(x)=\Phi\left[\gamma+\delta\cdot g\left(\frac{x-\xi}{\lambda}\right)\right]=\Phi(z), \qquad \text{(A-2)}$$

and the quantile is

$$x=\xi+\lambda\cdot g^{-1}\left(\frac{z-\gamma}{\delta}\right), \qquad \text{(A-3)}$$

where Φ is the cumulative standard normal distribution (i.e., with zero mean and unit variance).

The shape of the function $g(\cdot)$, which defines the four families of the Johnson transformation system and supports H of the four distributions, is given as

$$g(u)=\begin{cases}\log(u), & S_L \text{ log-normal family}, & H=[\xi,\infty]\\ \log\left(u+\sqrt{u^2+1}\right), & S_U \text{ unbounded family}, & H=[-\infty,\infty]\\ \log\left(u+\sqrt{u^2+1}\right), & S_B \text{ bounded family}, & H=[\xi,\xi+\lambda]\\ u, & S_N \text{ normal family}, & H=[-\infty,\infty]\end{cases}$$

$$\qquad \text{(A-4)}$$

$$g^{-1}(z)=\begin{cases}e^z & \text{for } S_L\\ e^z-e^{-z}/2 & \text{for } S_U\\ 1/1+e^{-z} & \text{for } S_B\\ z & \text{for } S_N\end{cases} \qquad \text{(A-5)}$$

$$g^{-1}(z)=\begin{cases}1/y & \text{for } S_L\\ 1/\sqrt{y^2+1} & \text{for } S_U\\ (1-y)/y & \text{for } S_B\\ 1 & \text{for } S_N\end{cases}. \qquad \text{(A-6)}$$

The most appropriate Johnson family for a specific sample can be evaluated from sample skewness and kurtosis by use of the following:

$$\begin{cases}(\omega-1)(\omega+2)^2=\hat{\beta}_1\\ \beta_2=\omega^4+2\omega^3+3\omega^2-3\end{cases}, \text{ then } \begin{cases}\hat{\beta}_2=\beta_2, & S_L \text{ family}\\ \hat{\beta}_2<\beta_2, & S_B \text{ family}\\ \hat{\beta}_2>\beta_2, & S_U \text{ family}\end{cases},$$

$$\qquad \text{(A-7)}$$

where β_1 and β_2 are the squared skewness and kurtosis, respectively, and the hat superscript indicates their sample estimates.

The methods and algorithm for the best fit on sample data are presented in Hill et al. (1976) (moment estimators), Wheeler (1980) (quantile estimators), and Swain et al. (1988) (least-square estimators). Quantiles are easily computed from distribution parameters (Eq. A-3), while expected value and variance can be computed explicitly for S_L and S_U and numerically for S_B (Draper 1952).

Important properties of the Johnson family of transformations are

- They can mimic a wide range of univariate distribution functions, ranging from unbounded to bounded.
- They can reproduce exactly the first four moments of any (feasible) statistical sample.
- They span the entire range of feasible values in the $[\beta_1, \beta_2]$ plane.

Appendix B: The Kappa Distribution

The four-parameter Kappa distribution has been proposed by Hosking (1994) as a generalization of the three-parameter distribution proposed by Mielke (1973), with the probability-density function

$$f(x)=\alpha^{-1}\left[1-\kappa(x-\xi)/\alpha\right]^{(1/\kappa)-1}\left[F(x)\right]^{1-h}, \qquad \text{(B-1)}$$

the cumulative distribution

$$F(x)=\left[1-h\left(1-\kappa\frac{x-\xi}{\alpha}\right)\right]^{\frac{1}{k}}, \qquad \text{(B-2)}$$

and the quantile

$$x(F)=\xi+\frac{\alpha}{\kappa}\left[1-\left(\frac{1-F^h}{h}\right)^{\kappa}\right]. \qquad \text{(B-3)}$$

Particular cases with $h=0$ and/or $\kappa=0$ are obtained as the limits for $h\to 0$ and $\kappa\to 0$ **(Table B-1).**

The supports of the distribution are defined as

$$\begin{array}{llll}\xi+\alpha\dfrac{1-h^{-\kappa}}{\kappa}\le x\le\xi+\dfrac{\alpha}{\kappa} & h\ne 0;\kappa\ne 0 & -\infty\le x\le\xi+\dfrac{\alpha}{\kappa} & h\le 0;\kappa>0\\ \xi+\alpha\log h\le x\le\infty & h\ge 0;\kappa=0 & -\infty\le x\le\infty & h\le 0;\kappa=0\\ \xi+\alpha\dfrac{1-h^{-\kappa}}{\kappa}\le x\le\infty & h>0;\kappa\le 0 & \xi+\dfrac{\alpha}{\kappa}\le x\le\infty & h\le 0;\kappa<0\end{array}$$

Interesting properties of the Kappa distribution are

- It can mimic a large number of unimodal distributions, ranging from unbounded to left/right bounded (Dupis and Winchester 2001; Hosking 1994).
- It spans a large area in the L-skewness and L-kurtosis plane—L-moment equivalent of the $[\beta_1, \beta_2]$ plane (Hosking 1996), ranging from the logistic distribution to the theoretical limit.

TABLE B-1—KAPPA DISTRIBUTION: CASES WITH h=0 AND/OR κ=0

	$h=0,\kappa\ne 0$	$h\ne 0,\kappa=0$	$h=0,\kappa=0$
$F(x)$	$\left[1-h\left(1-\kappa\frac{x-\xi}{\alpha}\right)\right]^{1/h}$	$e^{-\left(1-\kappa\frac{x-\xi}{\alpha}\right)^{\frac{1}{\kappa}}}$	$e^{-e^{\left(1-\kappa\frac{x-\xi}{\alpha}\right)}}$

TABLE B-2—ANALYTICAL COMPUTATION OF KAPPA-DISTRIBUTION MOMENTS

	$h > 0$	$h < 0$
$u_f'\left(1-\kappa\dfrac{x-\xi}{\alpha}\right)$	$h^{-(1-r\kappa)}\dfrac{\Gamma(1+r\kappa)\Gamma(1/h)}{\Gamma(1+r\kappa+1/h)}$	$(-h)^{-(1-r\kappa)}\dfrac{\Gamma(1+r\kappa)\Gamma(-rk-1/h)}{\Gamma(1-1/h)}$

- Distribution moments can be computed analytically (Winchester 2000), as in **Table B-2.**

Procedure and algorithms for the best fit of the Kappa distribution are described in Hosking (2000) (*L*-moments) and in Winchester (2000) (maximum likelihood). Interestingly, the Kappa distribution has the generalized extreme value and the three-parameter Pareto distributions as special cases, thus resulting in an appealing candidate in extreme-value analysis.

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