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ON THE ESTIMATION OF DIRECTIONAL WAVE SPECTRUM BASED ON STATIONARY VESSELS 1ST ORDER MOTIONS: A NEW SET OF EXPERIMENTAL RESULTS

João V. Sparano
Naval Arch. & Ocean Eng. Dept
Escola Politécnica – University of São Paulo

Eduardo A. Tannuri
Mechatronics Eng. Dept
Escola Politécnica – University of São Paulo

Alexandre N. Simos
Naval Arch. & Ocean Eng. Dept
Escola Politécnica – University of São Paulo

Vinícius L. F. Matos
Exploration and Production
Petrobras

ABSTRACT

The practicability of estimating directional wave spectra based on a vessel 1st order response has been recently addressed by several researchers. The interest is justified since on-board estimations would only require only a simple set of accelerometers and rate-gyros connected to an ordinary PC. The on-board wave inference based on 1st order motions is therefore an uncomplicated and inexpensive choice for wave estimation if compared to wave buoys and radar systems. The latest works in the field indicate that it is indeed possible to obtain accurate estimations and a Bayesian inference model seems to be the preferable method adopted for performing this task. Nevertheless, most of the previous analysis has been based exclusively on numerical simulations. At Polytechnic School, an extensive research program supported by Petrobras has been conducted since 2000, aiming to evaluate the possibility of estimating wave spectrum on-board offshore systems, like FPSO platforms. In this context, a series of small-scale tests has been performed at the LabOceano wave basin, comprising long and short crested seas. A possible candidate for on-board wave estimation has been recently studied: a crane barge (BGL) used for launching ducts offshore Brazil. The 1:48 model has been subjected to bow and quartering seas with different wave heights and periods and also different levels of directional spreading. A Bayesian inference method was adopted for evaluating the wave spectra based on the time-series of motions and the results were directly compared to the wave spectra measured in the basin by means of an array of wave probes. Very good estimations of the statistical parameters (significant wave height, peak period and mean wave direction) were obtained and, in most cases, even the directional spreading could be properly predicted. Inversion of the mean direction (180° shift), mentioned by some authors as a possible drawback of the Bayesian inference method, was not observed in any case. Sensitivity analysis on errors in the input parameters, such as the vessel inertial characteristics, has also been performed and attested that the method is robust enough to cope well with practical uncertainties. Overall results once again indicate a good performance of the inference method, providing an important additional validation supported by a large set of model tests.

NOMENCLATURE

ε_k - second order spectrum difference at direction k
ϕ_{mn} - cross spectra of ship motions "m" and "n"
θ – Wave direction $[0;2\pi]$
σ^2 - variance of the noise
ω - Frequency (rad/s)
A – Ship RAO matrix
B – Vector with cross spectra of ship motions
D – Matrix defined in (6)
$E(\omega)$ – Power spectrum
H_s – Significant wave heigth
J(x) – Function to be minimized by Bayesian Method
$L(x\,|\,B)$ - Likelihood function
P(x) – the prior probability of occurrence of the spectrum
RAOm – Response Amplitude Operator (Transfer Function) of ship motion "*m*"

$S(\omega, \theta)$ – Directional Wave Spectrum
Tp – Wave spectrum peak period
U – vector with measurenment noise
u – the parameter that controls the trade-off between good fit to the data and smoothness of the estimated spectrum.
u_{energy} – parameter used to minimize estimated wave spectrum energy.
$x = (S_1 \quad S_2 \quad \ldots \quad \ldots \quad S_K)^T$ - vector with the components of wave directional spectrum

INTRODUCTION

The on-line estimation of directional wave spectra is useful for offshore systems operation, since operational problems may be caused by high values of vertical wave-induced oscillations. The information about the wave spectra can be used in emergency procedures, aiming to reduce the risks of the operation and to keep the integrity of the installations. For example, such information can be used to relocate an FPSO to a safer wave heading, either using tugboats or dynamic positioning systems. Furthermore, the estimation is also useful for other types of ships, like crane barges and pipe-laying vessels, since the information can be used by the captain to evaluate the feasibility of the operation or the necessity to interrupt it.

Other application is related to Dynamic Positioning (DP). As offshore oil production moves towards deeper waters, DP systems become more important as an economical solution for the station-keeping of floating production units and other vessels. For DP operations under extreme conditions, feed forward control may represent a significant improvement in the efficiency of the system, concerning station-keeping behavior and fuel consumption. The feed forward control consists of providing information on the environmental excitation (waves, current and winds) to the system in order to predict the DP response required for counteracting the estimated environmental forces. The on-line estimation of directional wave spectrum may play an important role on the wave force feed forward control.

In the last 30 years, sea state measurements were carried out mainly by moored directional buoys. Such devices provide good estimates of wave spectrum, since they have negligible dynamics and their motions can be accurately measured by accelerometers and tilt sensors. However, buoys are easily subjected to damage and loss, and present practical and economical drawbacks related to deep water mooring system installation. Recently, wave-monitoring radar systems have been developed based on the analysis of temporal and spatial evolution of the radar backscatter information. These systems may be installed on board, eliminating the problems associated to moored buoys. However, they present several drawbacks, related to the high initial cost, complex computational hardware requirements and the influence of the meteorological conditions on its measurements.

The estimation of the spectrum based on ship motions measurements may overcome such problems since it requires simple instrumentation and computational hardware, and can be installed onboard. Some applications have already been described by Iseki and Ohtsu (2000), Tannuri et al. (2004) and Pascoal (2005), for example. Two main classes of algorithms were used to perform the estimation. The first class is based on the parametric description of the spectrum, the formulation of a non-linear minimization problem for the estimation of the unknown spectrum parameters. Problems related to convergence to non-optimal solution, long computational time and lack of robustness have been related in the literature (Pascoal, 2005). The second class does not consider any pre-defined shape of the spectrum, and each point is then freely estimated. Several estimation methods can be applied, and in any case, the resulting optimization problem is linear. A fast solution can then be obtained. Among the non-parametric approaches, the latest works in the field indicate that the utilization of a Bayesian inference model seems to be the preferable method adopted for performing the estimation (Simos, 2007).

Nevertheless, most of the previous analysis has been based exclusively on numerical simulations. At Escola Politécnica, an extensive research program supported by Petrobras has been conducted since 2000, aiming to evaluate the possibility of estimating wave spectrum on-board offshore systems, like FPSO platforms. In this context, a series of small-scale tests has been performed at the LabOceano wave basin, comprising long and short crested seas. A possible candidate for on-board wave estimation has been recently studied: a crane barge (BGL) used for launching ducts offshore Brazil. The 1:48 model has been subjected to bow and quartering seas with different wave heights and periods and also different levels of directional spreading.

The Bayesian inference method was adopted for evaluating the wave spectra based on the time-series of motions and the results were directly compared to the wave spectra measured in the basin by means of an array of wave probes. Very good estimations of the statistical parameters (significant wave height, peak period and mean wave direction) were obtained and, in most cases, even the directional spreading could be properly predicted. Inversion of the mean direction (180° shift), mentioned by some authors as a possible drawback of the Bayesian inference method, was not observed in any case.

Sensitivity analysis on errors in the input parameters, such as the vessel inertial characteristics, has also been performed and attested that the method is robust enough to cope well with practical uncertainties. Overall results once again indicate a good performance of the inference method, providing an important additional validation supported by a large set of model tests.

THE BAYESIAN METHOD

In this section the Bayesian estimation method will be briefly presented, focusing on its application to the wave spectrum estimation based on ship motions measurements (Iseki and Ohtsu, 2000).

Assuming linearity between waves and ship response, the cross spectra of ship motions (ϕ_{mn}) time series and the directional wave spectrum are related by the Response Amplitude Operators (RAO's) through the following integral:

$$\phi_{mn}(\omega) = \int_{-\pi}^{\pi} RAO_m(\omega,\theta).RAO_n^*(\omega,\theta).S(\omega,\theta).d\theta \text{ , (1)}$$

where RAO_m denotes the Response Amplitude Operator of the motion m at frequency ω and incidence direction θ and $S(\omega,\theta)$ denotes the directional wave spectrum.

The discrete expression of (1) is derived assuming the integrand to be constant on each interval $\Delta\theta$:

$$\phi_{mn}(\omega) = \Delta\theta \sum_{k=1}^{K} RAO_{mk}(\omega).RAO_{nk}^*(\omega).S_k(\omega), \qquad (2)$$

with $\Delta\theta = 2\pi / K$, $RAO_{mk}(\omega) = RAO_m(\omega,\theta_k)$, $S_k(\omega) = S(\omega,\theta_k)$ and $RAO_{nk}^*(\omega) = RAO_n^*(\omega,\theta_k)$.

Eq.(2) can be written, for each frequency ω , as:

$$\begin{bmatrix} \phi_{11} & \phi_{12} & \cdots & \phi_{16} \\ \phi_{21} & \phi_{22} & \cdots & \phi_{26} \\ \phi_{31} & \phi_{32} & \cdots & \phi_{36} \\ \phi_{41} & \phi_{42} & \cdots & \phi_{46} \\ \phi_{51} & \phi_{52} & \cdots & \phi_{56} \\ \phi_{61} & \phi_{62} & \cdots & \phi_{66} \end{bmatrix} = \Delta\theta \times \begin{bmatrix} RAO_{11} & RAO_{12} & \cdots & RAO_{1K} \\ RAO_{21} & RAO_{22} & \cdots & RAO_{2K} \\ RAO_{31} & RAO_{32} & \cdots & RAO_{3K} \\ RAO_{41} & RAO_{42} & \cdots & RAO_{4K} \\ RAO_{51} & RAO_{52} & \cdots & RAO_{5K} \\ RAO_{61} & RAO_{62} & \cdots & RAO_{6K} \end{bmatrix} \times \begin{bmatrix} S_1 & 0 & \cdots & 0 \\ 0 & S_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & S_K \end{bmatrix} \times \begin{bmatrix} RAO_{11}^* & RAO_{21}^* & \cdots & RAO_{61}^* \\ RAO_{12}^* & RAO_{22}^* & \cdots & RAO_{62}^* \\ \vdots & \vdots & \vdots & \vdots \\ RAO_{1K}^* & RAO_{2K}^* & \cdots & RAO_{6K}^* \end{bmatrix} \qquad (3)$$

It should be noticed that the left-side matrix $\mathbf{\Phi}(\omega)$ is Hermitian. Therefore, using only the upper triangular matrix and expressing real and imaginary parts separately, Eq.(3) can be reduced to the linear form:

$$\mathbf{B} = \mathbf{A}.\mathbf{x} + \mathbf{U} , \qquad (4)$$

where $\mathbf{U}$ is a vector representing measurement noise, assumed to be a Gaussian white noise sequence with zero mean value and variance σ^2, $\mathbf{x}$ is a vector with the unknown spectrum, $\mathbf{A}$ is the RAO matrix and $\mathbf{B}$ is the vector with the measurements given by:

$$\mathbf{B} = (\phi_{11} \;\; \phi_{22} \;\; \cdots \;\; \phi_{66} \;\; \mathrm{Re}(\phi_{12}) \;\; \cdots \;\; \mathrm{Re}(\phi_{16}) \;\; \mathrm{Re}(\phi_{23}) \;\; \cdots \;\; \mathrm{Re}(\phi_{26}) \;\; \mathrm{Re}(\phi_{34}) \;\; \cdots$$
$$\cdots \;\; \mathrm{Re}(\phi_{36}) \;\; \mathrm{Re}(\phi_{45}) \;\; \mathrm{Re}(\phi_{46}) \;\; \mathrm{Re}(\phi_{56}) \;\; \mathrm{Im}(\phi_{12}) \;\; \cdots \;\; \mathrm{Im}(\phi_{16}) \;\; \mathrm{Im}(\phi_{23}) \;\; \cdots$$
$$\cdots \;\; \mathrm{Im}(\phi_{26}) \;\; \mathrm{Im}(\phi_{34}) \;\; \cdots \;\; \mathrm{Im}(\phi_{36}) \;\; \mathrm{Im}(\phi_{45}) \;\; \mathrm{Im}(\phi_{46}) \;\; \mathrm{Im}(\phi_{56}))^T$$

$$\mathbf{A} = \begin{bmatrix} \|RAO_{11}^2\| & \|RAO_{12}^2\| & \cdots & \|RAO_{1K}^2\| \\ \vdots & \vdots & \vdots & \vdots \\ \|RAO_{61}^2\| & \|RAO_{62}^2\| & \cdots & \|RAO_{6K}^2\| \\ \mathrm{Re}(RAO_{11}RAO_{21}^*) & \mathrm{Re}(RAO_{12}RAO_{22}^*) & \cdots & \mathrm{Re}(RAO_{1K}RAO_{2K}^*) \\ \vdots & \vdots & \vdots & \vdots \\ \mathrm{Re}(RAO_{61}RAO_{51}^*) & \mathrm{Re}(RAO_{62}RAO_{52}^*) & \cdots & \mathrm{Re}(RAO_{6K}RAO_{5K}^*) \\ \mathrm{Im}(RAO_{11}RAO_{21}^*) & \mathrm{Im}(RAO_{12}RAO_{22}^*) & \cdots & \mathrm{Im}(RAO_{1K}RAO_{2K}^*) \\ \vdots & \vdots & \vdots & \vdots \\ \mathrm{Im}(RAO_{61}RAO_{51}^*) & \mathrm{Im}(RAO_{62}RAO_{52}^*) & \cdots & \mathrm{Im}(RAO_{6K}RAO_{5K}^*) \end{bmatrix}$$

$$\mathbf{x} = (S_1 \, S_2 \;\; \cdots \;\; \cdots \;\; S_K)^T$$

Applying the Bayesian procedure to the model (4), the unknown coefficients (vector $\mathbf{x}$) can be estimated by maximization of the product of the likelihood function by the prior distribution.

The likelihood function is the conditional probability of occurrence of a given measurement (matrix $\mathbf{B}$), given the directional spectrum (vector $\mathbf{x}$). Since measurement noise is assumed to be Gaussian, it can be shown that the likelihood function $L(\mathbf{x}|\mathbf{B})$ is given by:

$$L(\mathbf{x}|\mathbf{B}) = \left(\frac{1}{2\pi\sigma^2}\right)^{9/2} \exp\left(-\frac{1}{2\sigma^2}\|\mathbf{B} - \mathbf{A}\mathbf{x}\|^2\right). \qquad (5)$$

The prior distribution corresponds to the previous information about the unknown coefficients. Assuming that the spectrum is smooth with respect to the directions and defining the second order difference ε_k associate to direction *k* as:

$$\varepsilon_k = (x_k - 2.x_{k-1} + x_{k-2}) , \qquad (6)$$

the smoothness condition is equivalent to keeping the sum $\sum_{i=1}^{K} \varepsilon_i^2$ as small as possible. Considering that ε_k is a Gaussian variable, with zero mean value and variance σ^2 / u^2, the prior probability of occurrence of the spectrum x is given by:

$$\begin{aligned} P(\mathbf{x}) &= \left(\frac{u^2}{2\pi\sigma^2}\right)^{K/2} \exp\left(-\frac{u^2}{2\sigma^2}\sum_{k=1}^{K}\varepsilon_k^2\right) \\ &= \left(\frac{u^2}{2\pi\sigma^2}\right)^{K/2} \exp\left(-\frac{u^2}{2\sigma^2}\sum_{k=1}^{K}\|\mathbf{D}\mathbf{x}\|\right) \end{aligned} , \qquad (7)$$

where $\mathbf{D} = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 & 1 & -2 \\ -2 & 1 & 0 & \cdots & 0 & 0 & 1 \\ 1 & -2 & 1 & \cdots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & -2 & 1 \end{pmatrix}$

and u is the parameter that controls the trade-off between good fit to the data and smoothness of the estimated spectrum.

The product of likelihood function (5) by the prior distribution (7) is given by:

$$L(\mathbf{x}|\mathbf{B}).P(\mathbf{x}) = \left(\frac{u^2}{2\pi\sigma^2}\right)^{K/2}\left(\frac{1}{2\pi\sigma^2}\right)^{9/2}\exp\left(-\frac{1}{2\sigma^2}\left(\|\mathbf{B}-\mathbf{A}\mathbf{x}\|^2 + u^2\|\mathbf{D}\mathbf{x}\|\right)\right). \quad (8)$$

The maximization of expression (8) is equivalent to the minimization of the term inside the exponential. An extra term, called "u_{energy}", must be included in order to avoid the estimation of not-null wave spectrum for frequencies in which both the RAO and the ship response are nulls. So, the Bayesian estimate of the spectrum is the vector $\mathbf{x}$ which minimizes the function $J(\mathbf{x})$ given by:

$$J(\mathbf{x}) = \|\mathbf{B}-\mathbf{A}\mathbf{x}\|^2 + u^2\|\mathbf{D}\mathbf{x}\|^2 + u_{energy}\|\mathbf{x}\|^2.$$

A quadratic programming algorithm was used to perform this minimization.

NUMERICAL IMPLEMENTATION

The Bayesian Method previously exposed was implemented using MATLAB 7.0.

The Welch's Method was used for the estimation of motions power and cross spectra based on the time series. Each motion record is divided into eight sections with 50% overlap, each section being filtered by a Hanning window.

Figures 1 and 2 show an example of the time series for the 6 motions of the vessel and the power spectrum obtained by the Welch's Method. It can be clearly noticed that the spectrum estimates are not smooth along the frequencies, and a moving average filter is then applied after the Welch's estimation (red lines in Figure 2). Furthermore, since the low frequency motions are not taken into account in the Spectrum Estimation, a high pass filter with 0.222Hz cut-off frequency is also applied (such frequency corresponds to a period of 45s).

The Bayesian Method parameter u was calibrated using exhaustive numerical analysis and experimental results. As a general result, it could be inferred that the larger the level of the wave induced motions, the smaller is the sensitivity of the spectrum estimation considering variations in the parameter u. Furthermore, the calibration procedure indicated that larger values of the parameter must be used for larger vessels, in order to achieve good estimation of wave statistics (significant height, peak period and mean direction). Consequently, for larger vessels the estimation of wave spreading may be degraded, since the estimated wave spectrum gets smoother than the real one. For the crane barge considered in the present paper, the value u=0.0044 was obtained after the full calibration procedure.

A similar procedure was applied for the calibration of the parameter u_{energy}, and the optimal value of 0.0004 was obtained for the crane barge.

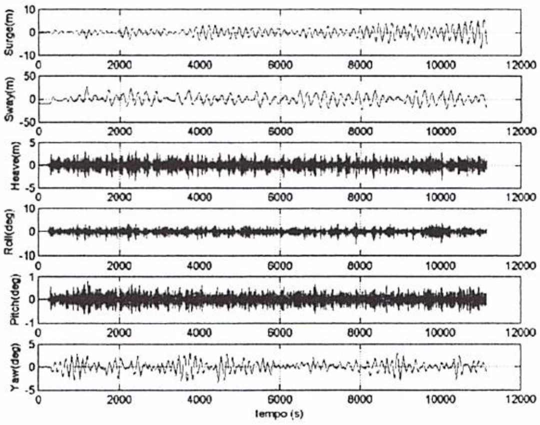

Figure 1. Example of motion time series

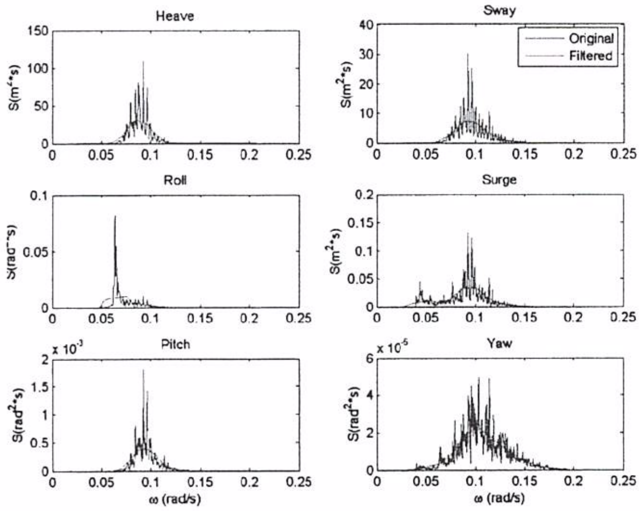

Figure 2. Power spectrum estimation (red – after the moving average filter)

The Bayesian Method was applied considering surge, sway, heave, pitch and yaw motions. The roll motion was not considered due to the inherent uncertainties regarding its transfer function.

EXPERIMENTAL SET-UP

Model tests were carried out in LabOceano main tank, a 45m length, 30m wide, 15m depth ocean basin. It is equipped with multi-directional wave generators, based on an in-line array of 75 flaps which allow emulating short-crested seas or the combination of two different unidirectional seas. Figure 3 shows a sketch of the LabOceano wave tank and the coordinate system adopted for the analysis. It also illustrates the angle convention used to define wave direction.

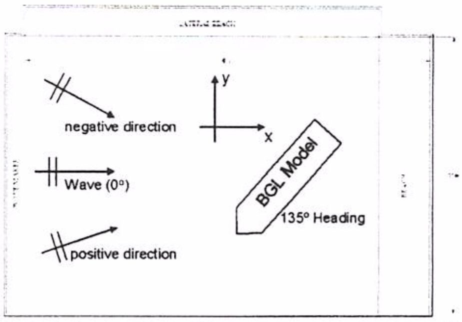

Figure 3. LabOcean Coordinate system and wave direction

A wave probe array is used to measure the incident wave elevation in 8 locations. Following Stansberg (1998), the Maximum Entropy Method is then applied in order to estimate the directional spectra that will set the basis of comparison for the spectra estimated using the ship motions. A full description of the wave calibration procedure is given in Tannuri et al. (2007).

The BGL crane barge main properties (real scale and 1:48 model scale) are presented in Table 1. Figure 4 shows the 1:48 model used in the experiments.

Table 1 BGL main properties

Properties	Real Scale	Model Scale
Mass (M)	17500 ton	158 kg
Moment of inertia (I_{xx})	2.60×10^{6}ton.m^2	10.20 kg.m^2
Moment of inertia (I_{yy}, I_{zz})	1.57×10^{7}ton.m^2	6.16 kg.m^2
Length (L)	120 m	2.5 m
Draft (T)	5.00 m	0.10 m
Breadth (B)	30.48 m	0.64 m
Heave natural period (T_{n33})	8.0 s	1.15 s
Roll natural period (T_{n44})	7.0 s	1.01 s
Pitch natural period (T_{n55})	10.0 s	1.44 s

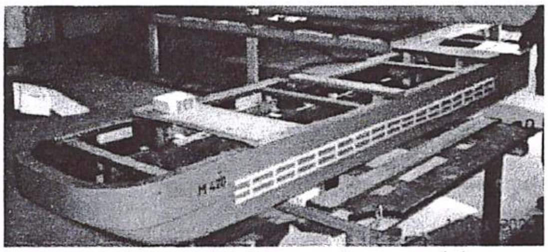

Figure 4. BGL crane barge model

The barge RAO's were obtained using a wave-body interaction software (WAMIT®, 2000). For example, Figure 5 shows the amplitude of RAO's for 90°, 135° or 180° incidence, considering the six degrees of freedom of the barge.

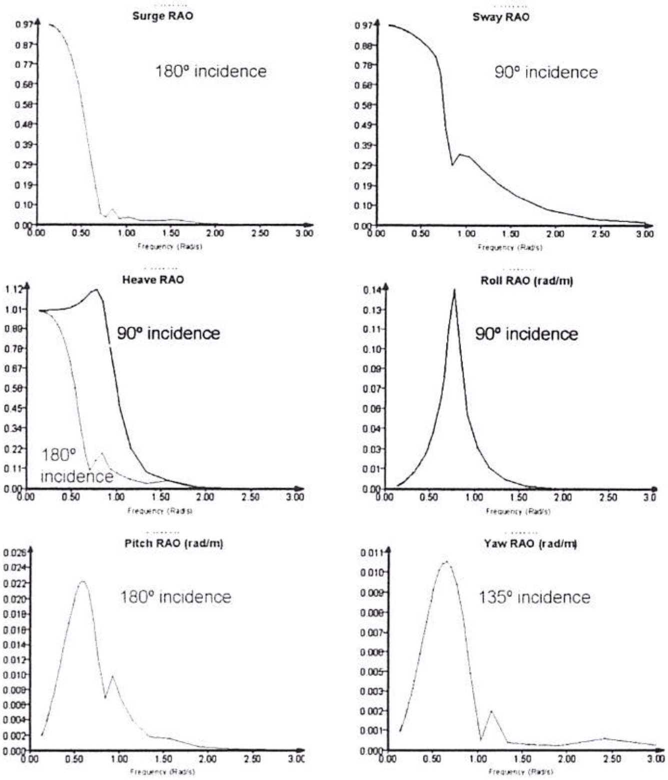

Figure 5. RAO's of the BGL crane barge

The whole set of waves used for the experimental set is listed in the Table 2 (all values in model scale).

EXPERIMENTAL RESULTS

As mentioned in the previous section, the LabOceano basin has its own referential frame, from which the incident waves were generated and calibrated. However, the Bayesian Method estimates the incoming waves related to the vessel local referential frame, following to the usual convention presented in Figure 6.

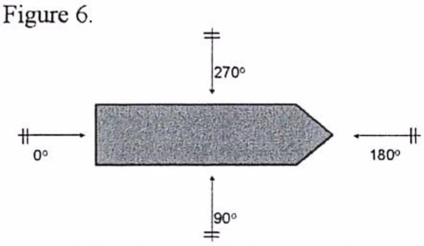

Figure 6. Vessel Local Ref. Frame Convention

Thus, according to this convention and Figure 3, Table 3 shows the results obtained from the 5 motion Bayesian Estimation Method applied to the BGL-1 barge model:

Table 2: Set of Waves for Experimental Tests at LabOcean – Theoretical Values

Test	*Type*	*Hs (m)*	*Tp (s)*	*Gamma*[1]	*Direction (°) - tank coord. System*
T41_70100		0.094	1.49	1.51	0
T41_70201	Irregular	0.163	2.22	1.70	0
T41_70301		0.094	1.49	1.51	0
T41_70400		0.094	1.49	1.51	0
T42_60100		0.031	1.67	1.4	-30
		0.021	0.96	0.9	30
T42_60200		0.042	1.06	1.6	-30
		0.015	1.34	2.0	15
T42_60300		0.031	0.77	1.3	-30
	Bimodal	0.013	1.63	2.2	30
T42_60400		0.042	1.65	1.5	-30
		0.021	1.65	1.2	30
T42_60500		0.031	1.67	1.4	-30
		0.021	0.96	0.9	-30
T43_70100		0.094	1.49	1.51	0
T43_70200	Irregular	0.163	2.22	1.70	0
T43_70300		0.094	1.49	1.51	0
T43_70400		0.094	1.49	1.51	0
T44_60100		0.031	1.67	1.4	-30
		0.021	0.96	0.9	30
T44_60200		0.042	1.06	1.6	-30
		0.015	1.34	2.0	15
T44_60300	Bimodal	0.031	0.77	1.3	-30
		0.013	1.63	2.2	30
T44_60400		0.042	1.65	1.5	-30
		0.021	1.65	1.2	30
T44_60500		0.031	1.67	1.4	-30
		0.021	0.96	0.9	-30

Table 3: Experimental Results of the Bayesian Estimation for the BGL-1

		Experimental			Bayesian Method			Errors		
Case	**Type**	**Hs (m)**	**Tp (s)**	**Dir (°)**	**Hs (m)**	**Tp (s)**	**Dir (deg)**	**Hs (%)**	**Tp (%)**	**Direction (°)**
'T41_70100'		0,09	1,57	90,94	0,10	1,48	89,62	-11,32	5,91	1,32
'T41_70201'	Irregular	0,17	2,24	92,19	0,18	2,08	91,56	-6,03	7,00	0,63
'T41_70301'		0,10	1,43	90,48	0,11	1,38	88,16	-12,87	3,38	2,32
'T41_70400'		0,09	1,49	91,43	0,10	1,48	87,29	-8,73	0,86	4,14
'T42_60100'		0,03	1,65	120,81	0,03	1,58	117,11	2,75	4,39	3,70
'T42_60200'	Bimodal	0,04	1,08	109,56	0,04	1,08	106,56	-7,32	0,39	3,00
'T42_60300'		0,03	0,77	119,97	0,03	0,77	126,93	-3,73	-0,61	-6,96
'T42_60400'		0,04	1,65	119,33	0,04	1,58	115,43	-0,74	4,39	3,90
'T42_60500'		0,03	1,74	105,61	0,03	1,58	110,01	-5,69	9,34	-4,40
'T43_70100'		0,09	1,57	135,94	0,10	1,58	126,17	-8,48	-0,48	9,77
'T43_70200'	Irregular	0,17	2,24	137,19	0,19	2,28	126,63	-11,90	-1,97	10,56
'T43_70300'		0,10	1,43	135,48	0,10	1,48	124,29	-3,75	-3,66	11,19
'T43_70400'		0,09	1,49	136,43	0,09	1,48	126,77	2,73	0,86	9,66
'T44_60100'		0,03	1,65	150,81	0,03	1,68	140,32	1,99	-1,69	10,49
'T44_60200'	Bimodal	0,04	1,08	139,56	0,04	0,98	132,70	1,56	9,68	6,87
'T44_60300'		0,03	0,77	149,97	0,02	0,77	156,87	1,58	-0,61	-6,90
'T44_60400'		0,04	1,65	149,33	0,04	1,58	142,40	0,12	4,39	6,94
'T44_60500'		0,03	1,74	135,61	0,03	1,68	127,27	-4,07	3,57	8,34

[1] Here we assume a JONSWAP spectrum type.

As it can be noticed, the T41 and T43 cases are essentially the same waves, but with a different vessel heading; the same applies to cases T42 and T44.

Also, for bimodal seas, both the Maximum Entropy Method - used to calibrate the experimental waves - and the Bayesian Method estimate Hs, Tp and Mean Direction only for the combined spectrum, instead of each peak separately as shown in Table 2.

The analysis of the table above shows a very good agreement between experimental and estimated results, with maximum errors in Hs, Tp and direction of, respectively, 12%, 10% and 11°.

Figures 8,9,10 and 11 show graphical results for four different cases extracted from the table above. All the graphical results shown on Table 3 can be found in Sparano (2007).

The plot (a) is the contour map of the experimental spectrum, estimated by the 8 probe array as mentioned in the Experimental Set-up Section. Its peak is related to the tank coordinate system (Figure 3), just like the peak of plot (b), the estimated spectrum.

However, the vessel heading to the tank coordinate system (plot (d)), results, as estimated direction according to Figure 6, 91.56° in Figure 7, 126.63° in Figure 8, 126.93° in Figure 9 and 156.87° in Figure 10. Plot (c) is the power density spectrum of both experimental and estimated spectra.

Results show that the method was able to provide precise estimations of wave direction for unimodal sea conditions for different wave headings (Fig.7 and Fig.8). Fig.9 corresponds to a condition when two different quartering long-crested seas with different peak periods hit the vessel. Energy and mean direction are once again accurately estimated. Finally, Fig.10 presents a situation with two different seas with different peak periods coming from distinct directions. This is a very demanding situation regarding the spectrum prediction and the level of agreement obtained confirms that the estimation procedure based on the vessel motions is able to provide good quality outcomes even for these challenging conditions.

CONCLUSIONS

A very extensive set of experiments with the BGL-1 barge were carried out at the LabOceano basin in order to verify the accuracy of the Bayesian Method for estimating directional wave spectra based on 1st order vessel motions.

The theoretical wave parameters were listed on Table 2, and the paradigm wave spectra at the basin tank were obtained from an 8 point wave-probes array, using the Maximum Entropy Method as proposed by Stansberg (1998).

The results presented on Table 3 show a very good agreement between experimental (expected) and estimated values, regarding the main wave spectrum statistics, i.e, significant wave high, peak period and mean direction of incidence, with maximum errors of, respectively, 12%, 10% and 11°, the latest one for an unimodal sea with high energy spreading (see Table 2).

Indeed, as the BGL-1 RAOs has a cut-off frequency around 2 rad/s (frequency above there is no more vessel motion), it is possible to estimate the directional spectrum with a relatively high range of frequencies, as it can be seen specially at Figure 10, as well as its directional spreading. In other words, the 5 motion Bayesian Method applied at the BGL-1 allows estimating directional wave spectra with low peak periods and high values of directional spreading due to the barge high level of motions, fact which wouldn't be seen at an FPSO for example, because the latter filters the spectrum high frequency components, i.e, its cut-off frequency is lower than 2 rad/s. For the bimodal cases, specially the one described by Figure 9, although the estimated statistics are the one of the combined spectrum, it can be seen both peaks at Figures 9-b and 9-c, with a good agreement on that also.

It is very important to mention the role played by the parameters "u" and "u_{energy}" in the spectrum estimation problem, as explained at the "Numerical Implementation" section. These parameters may be adjusted for each vessel or loading condition through sensitivity analysis and this procedure usually provides an improvement of the statistical outcome, especially for systems with relatively low 1st order response, as is the case of a loaded FPSO, for example. Results, however, are not very sensible to the external parameters and the selection of their values may be understood as a "fine-tuning" of the method.

The whole set of experimental results confirms the feasibility of estimating directional wave spectra based on 1st order vessel motions using the Bayesian Method described herein this paper. Obviously, for an accurate spectrum estimation, the vessel must have a reasonable response face to the waves that it wishes to estimate. The range of wave spectra that can be estimated increases as the vessel motion levels on waves increases, that is, if the vessel responds well for a relatively high range of frequencies.

The quality of the spectrum statistics estimations is also related to the correct evaluation of the RAOs, although the Bayesian Method has proved to be only weakly influenced by errors that are likely to occur on the RAO evaluation (Tannuri, 2001).

Other offshore systems can be used for estimating directional wave spectrum using the Bayesian approach, provided their RAOs are known and a set of accelerometers and rate-gyros is installed on board in order to collect motion data. The range of possible applications, however, is much more wide and might also include vessels with forward speed (as studied by Iseki (2004), for example) when, roughly speaking, corrections on the wave encounter frequency must be made.

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T41_70201	Experimental	Bayesian	Errors
Hs (m)	0.17	0.18	-6.03%
Tp (s)	2.24	2.08	7.00%
Direction (°)	92.19	91.56	0.63°

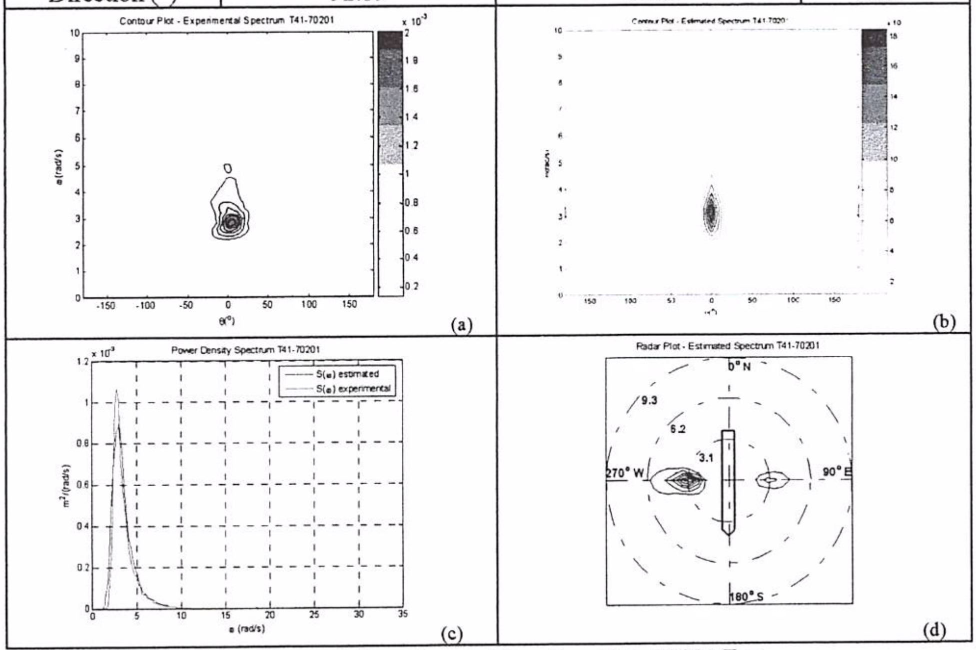

Figure 7: Experimental Results – T41_70201 Test

T43_70200	Experimental	Bayesian	Errors
Hs (m)	0.17	0.19	-11.90%
Tp (s)	2.24	2.28	-1.97%
Direction (°)	137.19	126.63	10.56°

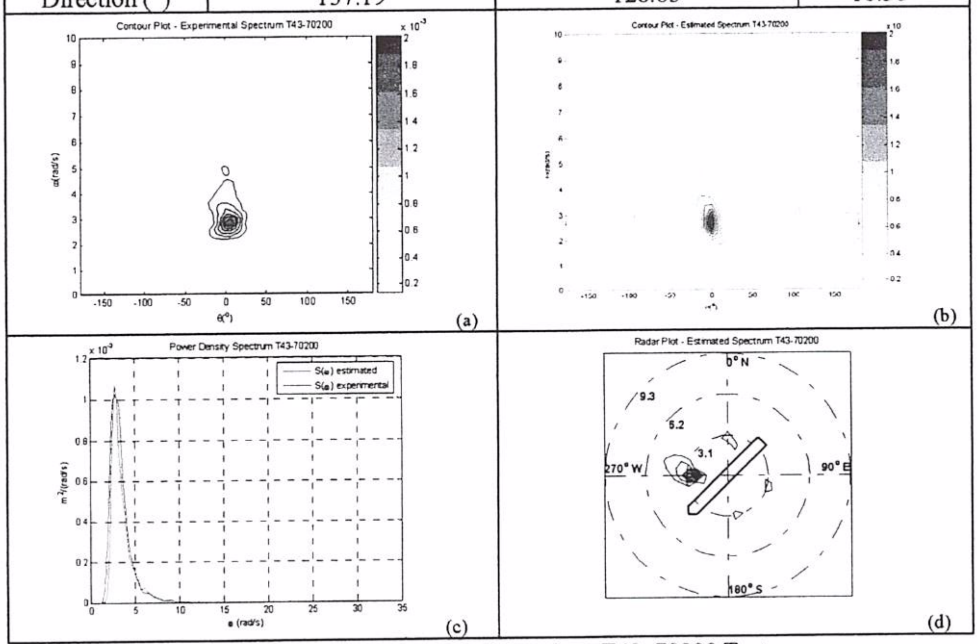

Figure 8: Experimental Results – T43_70200 Test

T42_60200	Experimental	Bayesian	Errors
Hs (m)	0.03	0.03	-3.73%
Tp (s)	0.77	0.77	-0.61%
Direction (°)	119.97	126.93	-6.96°

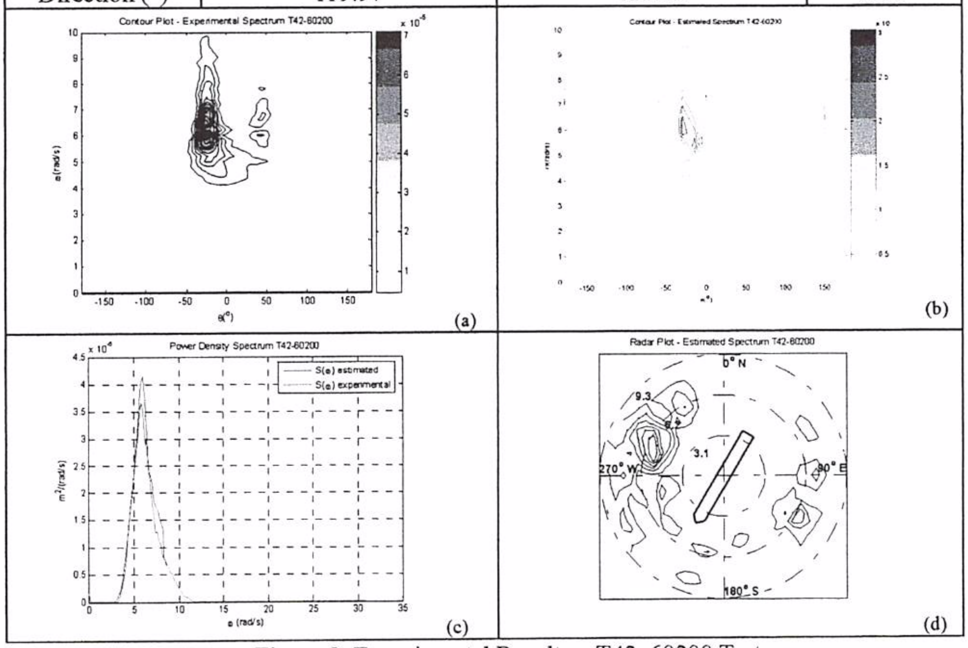

Figure 9: Experimental Results – T42_60200 Test

T44_60300	Experimental	Bayesian	Errors
Hs (m)	0.03	0.02	1.58 %
Tp (s)	0.77	0.77	0.61 %
Direction (o)	149.97	156.87	-6.90°

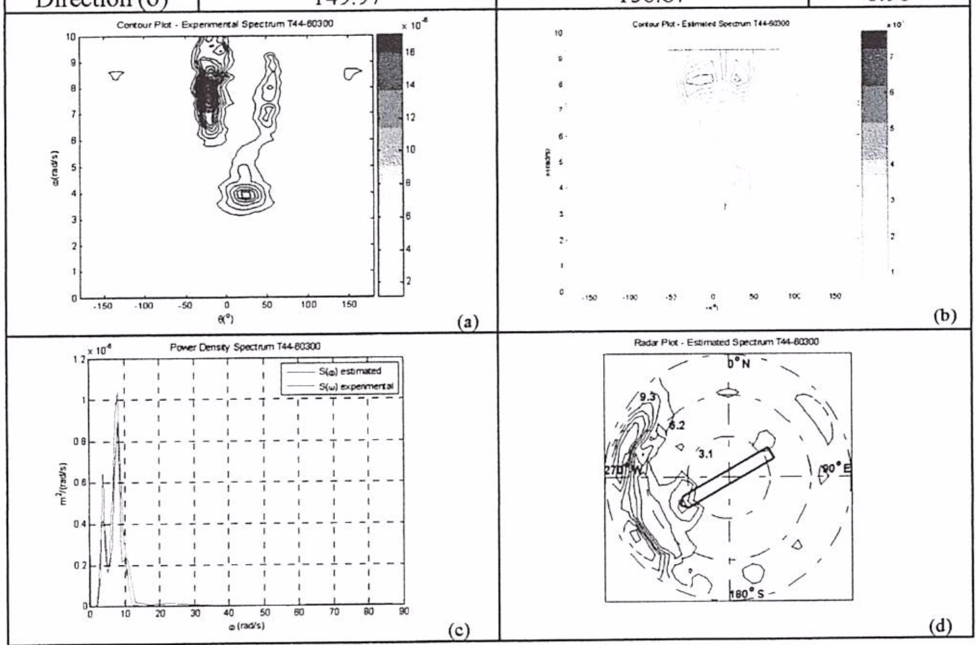

Figure 10: Experimental Results – T44_60300 Test

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