PhD thesis

Estimation of waves and ship responses using ship-board measurements

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In collaboration with:

NK classification society

Contents

Introduction: Decision Support System

Excessive wave-induced motions, accelerations and stresses, may increase the risk of:

- Capsizing;
- Large roll motion;
- Fatigue damage;
- Structural damage;
- Damage of equipment on deck;
- Loss or shift of cargo;
- Sea sickness;
- …

How to reduce the risks?

✓ Making decision on the heading and the speed of the ship by use of:

1. Wave data
2. Estimation of ship responses (sea keeping, structural loads, added resistance, …)
3. Statistical predictions of expected responses in a time horizon of 20-60 minutes

Decision Support System

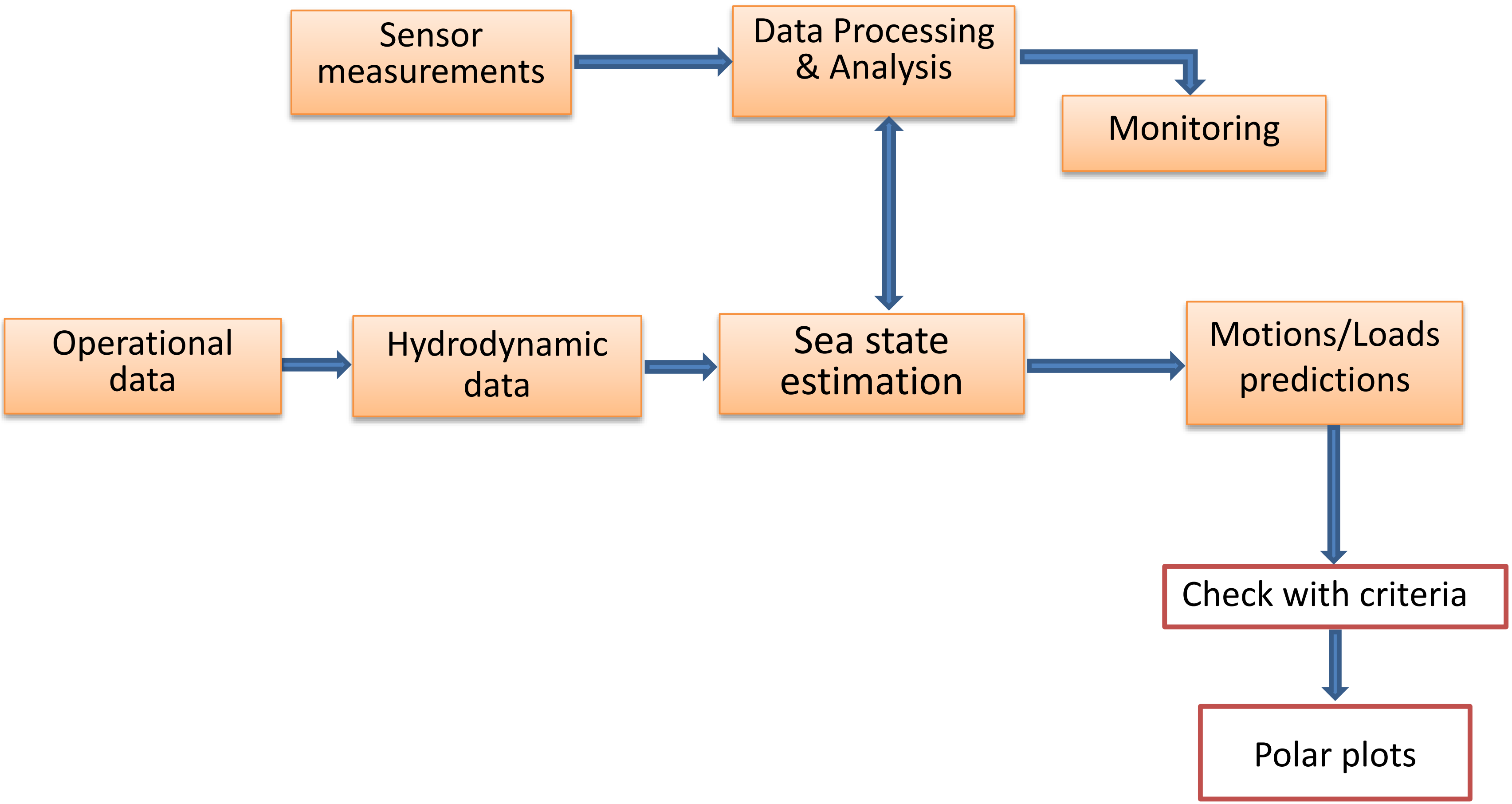
Tools for estimation of waves

- Wave rider buoys
- Marine radar
- Satellite measurements
- **Measured ship responses**

The advantage of the last method is that:

- ✓ the instrumentation is simple and inexpensive compared to other means.
- ✓ The wave data can be provided real-time and at the actual position of the ship.

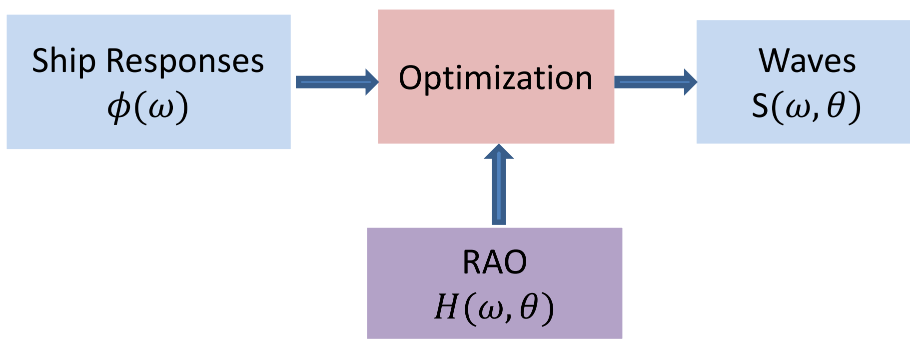
Wave estimation using ship responses

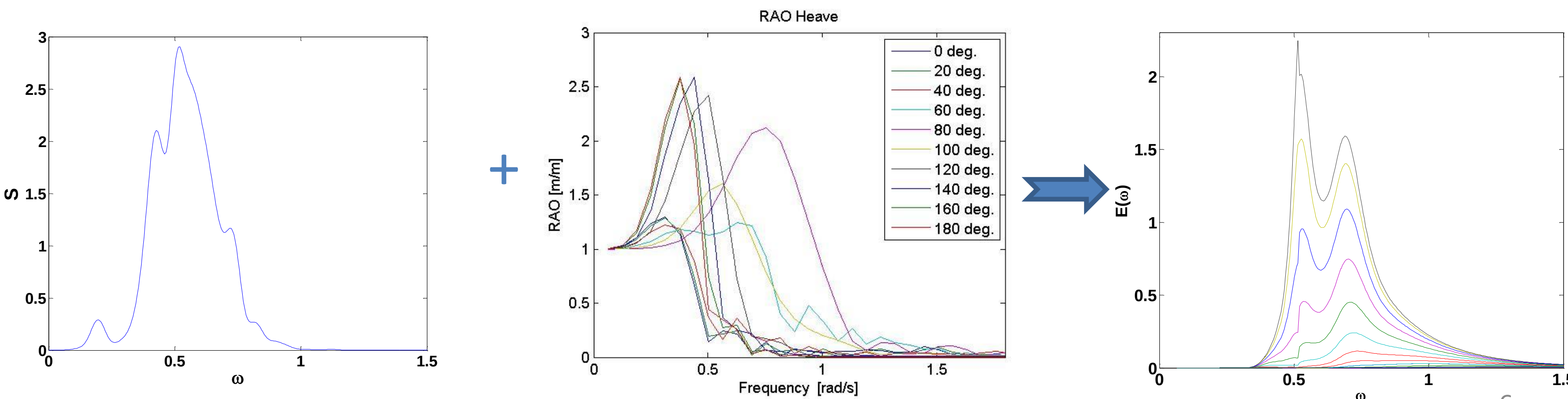


Wave estimation using ship responses

- A ship can act as a wave buoy.
- The theoretical relationship between the spectral density of a ship response and the directional wave spectrum is given by:

$$\Phi(\omega) = \int_{-\pi}^{\pi} |H(\omega,\theta)|^2 \, S(\omega,\theta) \, d\theta$$





Model description

Optimization problem based on spectral moments

- The amount of energy of the responses should be conserved whether using measured signals or theoretical calculations.

$$\bar{\Phi}_{ij}(\omega_e)\delta\omega_e = \Phi_{ij}(\omega)\delta\omega$$

$$\int_{\omega_{e_l}}^{\omega_{e_h}} \bar{\Phi}_{ij}(\omega_e)d\omega_e = \int_{\omega_l}^{\omega_h}\int_{-\pi}^{\pi} H_i(\omega,\theta)H_j^*(\omega,\theta)S(\omega,\theta)\,d\theta d\omega, \quad i,j=1,2,...,N$$

- Higher order moments can also be used as well

$$\int_{\omega_{e_l}}^{\omega_{e_h}} \omega_e^n\bar{\Phi}_{ii}(\omega_e)d\omega_e = \int_{\omega_l}^{\omega_h}\int_{-\pi}^{\pi}(\omega-\frac{V}{g}\omega^2 cos(\theta))^n\,|H_i(\omega,\theta)|^2\,S(\omega,\theta)\,d\theta d\omega, \quad n=1,2,...$$

- A number of responses (N) are used to establish the set of objective functions.

Model description

Parametric modeling approach

- There are different methods including parametric and non-parametric to solve the above obtimizaion problem.
- In the parametric method, the wave spectrum, S, is assumed to follow a standard e.g. JONSWAP model:

$$S(\omega) = \frac{\alpha g^2}{\omega^5} exp[-\frac{5}{4}(\frac{\omega_p}{\omega})^4]\gamma^{exp[\frac{-(\frac{\omega}{\omega_p}-1)^2}{2\sigma^2}]}$$

$$\alpha \approx 5.061\frac{H_s^2}{T_p^4}[1-0.287ln(\gamma)] \quad , \quad \omega_p = \frac{2\pi}{T_p}$$

- Short-crested waves are considered:

$$S(\omega,\theta) = S(\omega)D(\omega,\theta)$$

- With a spreading function as:

$$D(\omega,\theta) = N(s)cos^{2s}(\frac{\theta-\mu}{2})$$

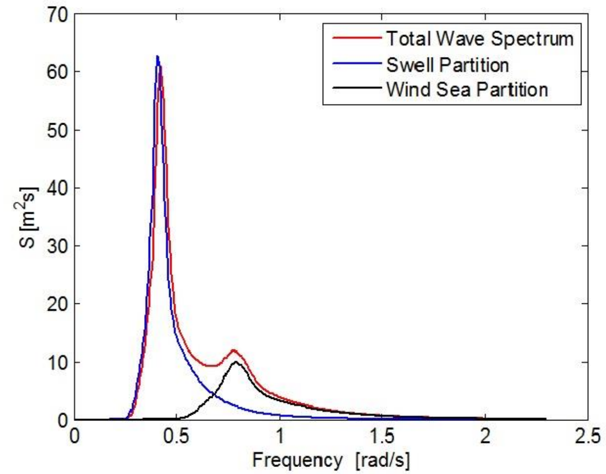
μ : relative mean wave direction
ω: wave frequency
θ: relative wave direction
ω_p: peak frequency
S: spreading parameter
γ: peakedness factor

Model description

Spectral partitioning and inequality constraints

- Identification of swell and wind-sea components

$$S(\omega,\theta) = S_w(\omega,\theta) + S_{sw}(\omega,\theta)$$



- The current wind information can be used for partitioning:
- Separation frequency in the spectrum:

$$\omega_s = \frac{g}{\beta U_w}$$

- General wave steepness constraint:

$$11.4\sqrt{\frac{H_s}{g}} < T_p$$

- Lower bound for wind sea steepness:

$$T_p < 15.7\sqrt{\frac{H_s}{g}}$$

- Additional constraint for wave direction estimation:

$$|\theta_\omega - \mu| < 90°$$

U_w: wind speed
β: empirical constant
g: gravity acceleration
θ_ω: relative wind direction
μ: relative mean wave direction

Global Optimization

- The fitting process is set by the difference between the measured and the theoretical spectral moments normalized by the measured moment (variance) of the response.

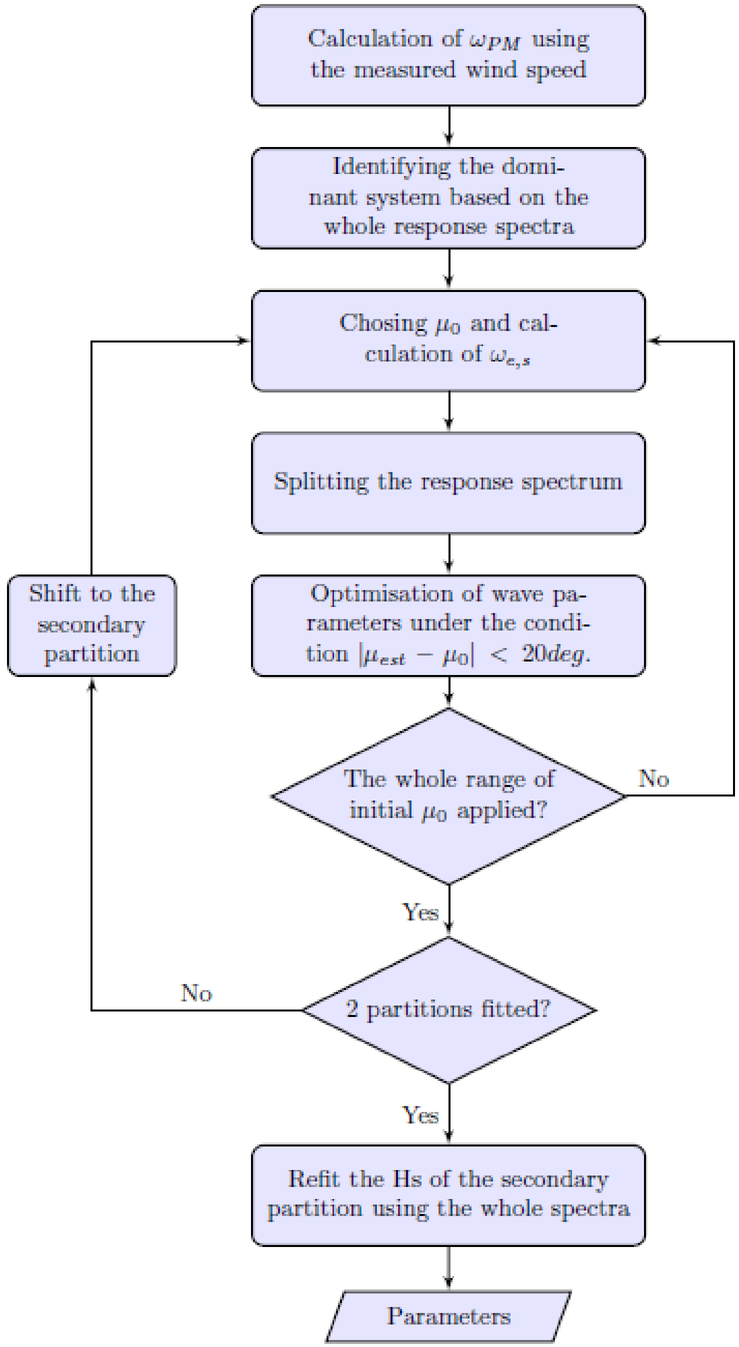
$$m_{0,ij} = \delta\theta\delta\omega \sum_{k=1}^{K}\sum_{l=1}^{L} H_i(\omega_k, \theta_l) H_j^*(\omega_k, \theta_l) S(\omega_k, \theta_l) \qquad \boldsymbol{i, j = 1, 2, \ldots, N}$$

- Optimization is based on some of squared residuals for all considered responses.

$$SSR = \sum_{i=1}^{N}\sum_{j=1}^{N} \frac{1}{(m_{0,ij})^2} [m_{0,ij} - \delta\theta\delta\omega \sum_{k=1}^{K}\sum_{l=1}^{L} H_i(\omega_k, \theta_l) H_j^*(\omega_k, \theta_l) S(\omega_k, \theta_l)]^2$$

- Vertical motion, pitch, sway and vertical bending moment are used according to experience and literature.
- Global optimizaion is applied using Multi-Start and Genetic algorithm in matlab.
- The wave parameters (Hs, Tp, μ, ...) are then estimated.

Global Optimization
Flowchart

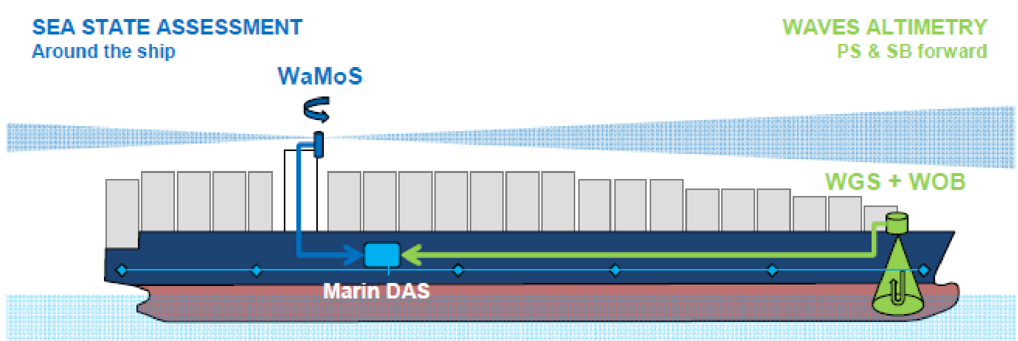


Case study I: 9400 TEU container ship

Parameter	Dimension
Overall Length	349.0 m
Beam	42.8 m
Maximum Draught	15.0 m
DWT	113,000 ton
Capacity	9415 TEU
Operational Draft	14.2 m
Operational Speed	21.0-23.5 kn

Other equipment for onboard wave estimation:

1. An X-band radar from WAMOS® (Wave and current Monitoring System)
2. Wave radar from RADAC® called wave guide system



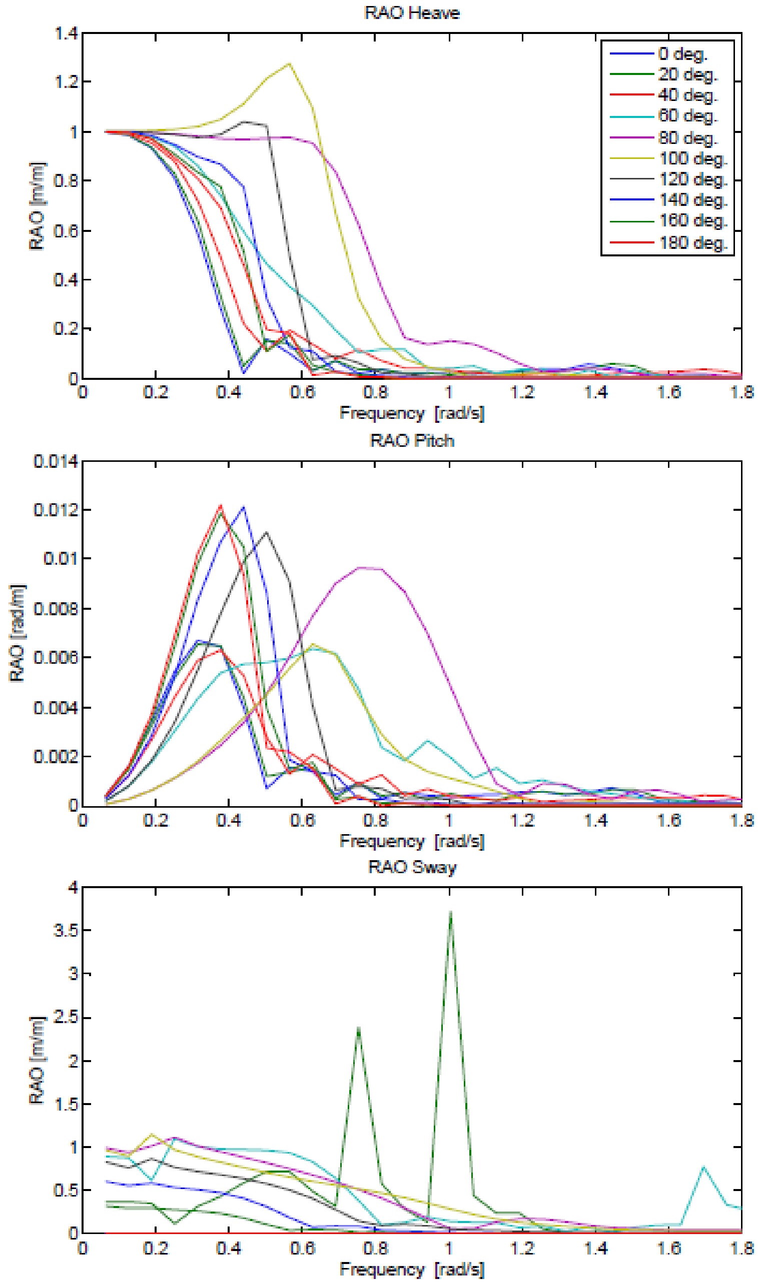
Wave estimation based on numerical simulations

For various wave scenarios, the responses were generated using JONSWAP spectra and the corresponding transfer functions.

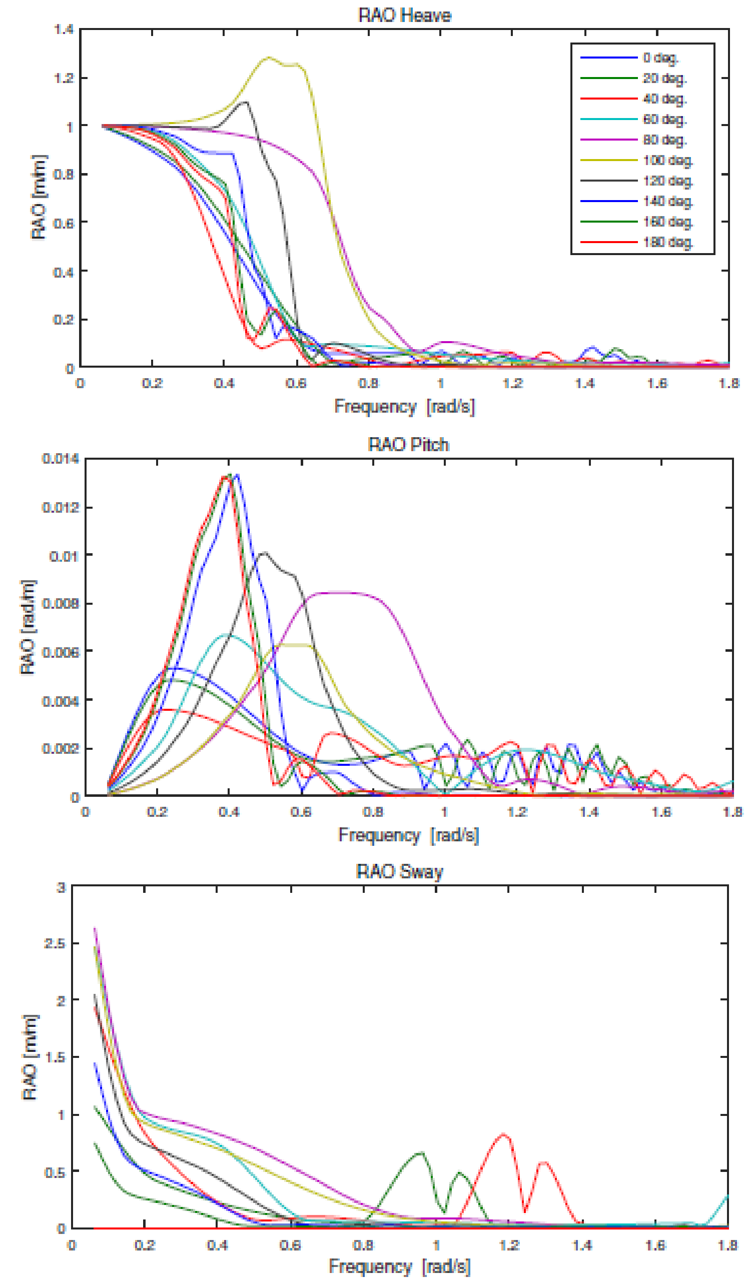
Cases	Wind sea					Swell					Wind Speed
	H_s(m)	T_p(s)	μ(deg.)	s_{max}	γ	H_s(m)	T_p(s)	μ(deg.)	s_{max}	γ	U_w(m/s)
A,B,C,D	3	8	45,90,135,180	10	2	0	—	—	—	—	14
E,F,G,H	0	—	—	—	—	5	15	45,90,135,180	25	4	5
I,J,K,L	3	8	45,-90,135,90	10	2	5	15	-135,90,45,180	25	4	14
M,N,O,P	3	8	45,-90,135,90	10	2	2	12	-135,90,45,180	25	4	14

We used 2 different sets of RAOs in wave estimation to consider hydrodynamic uncertainties. RAO1 is based on panel method whereas RAO2 is based on linear strip theory

RAO1


RAO Heave
RAO [m/m]
Frequency [rad/s]
0 deg.
20 deg.
40 deg.
60 deg.
80 deg.
100 deg.
120 deg.
140 deg.
160 deg.
180 deg.
RAO Pitch
RAO [rad/m]
Frequency [rad/s]
RAO Sway
RAO [m/m]
Frequency [rad/s]

RAO2


RAO Heave
RAO [m/m]
Frequency [rad/s]
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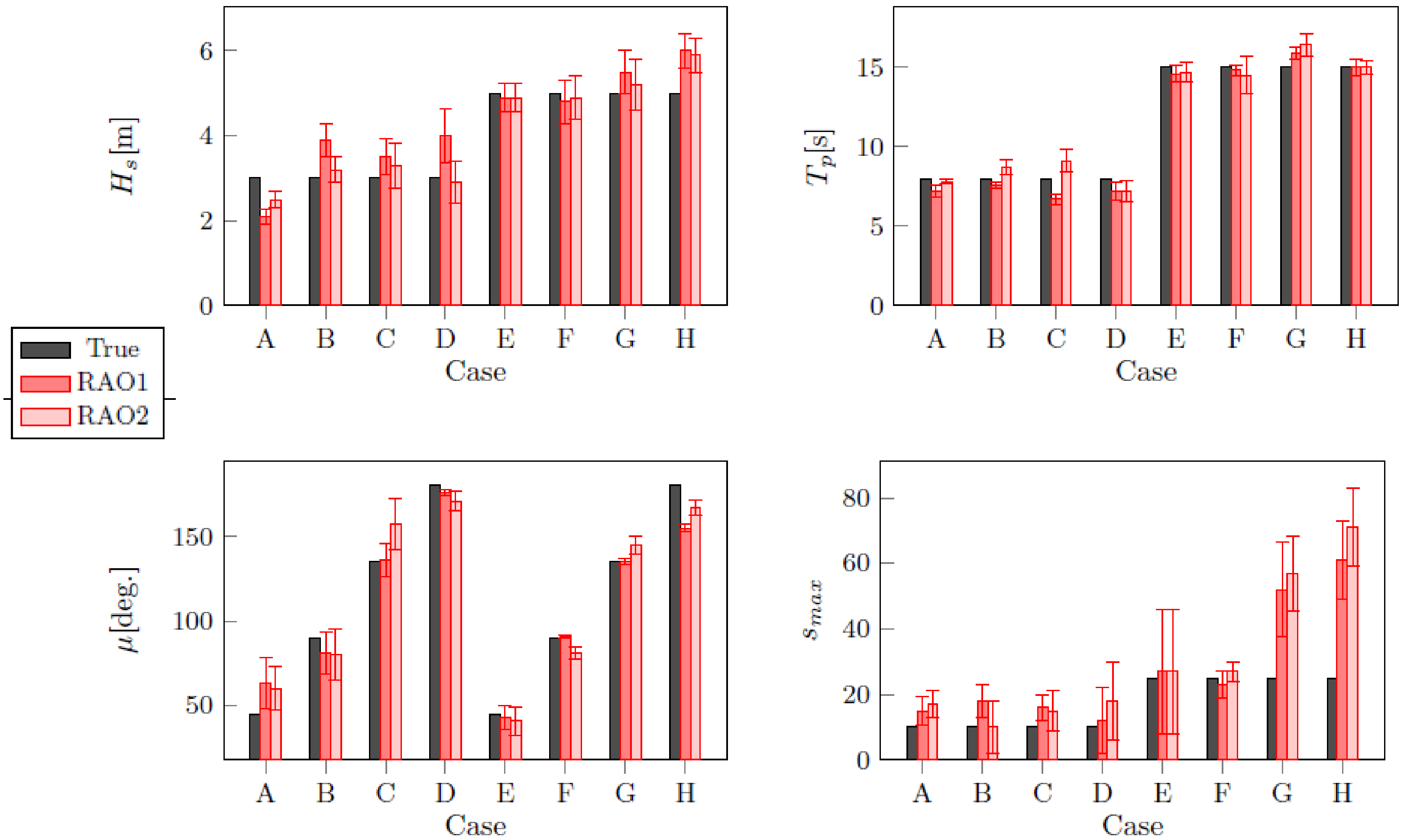
140 deg.
160 deg.
180 deg.
RAO Pitch
RAO [rad/m]
Frequency [rad/s]
RAO Sway
RAO [m/m]
Frequency [rad/s]

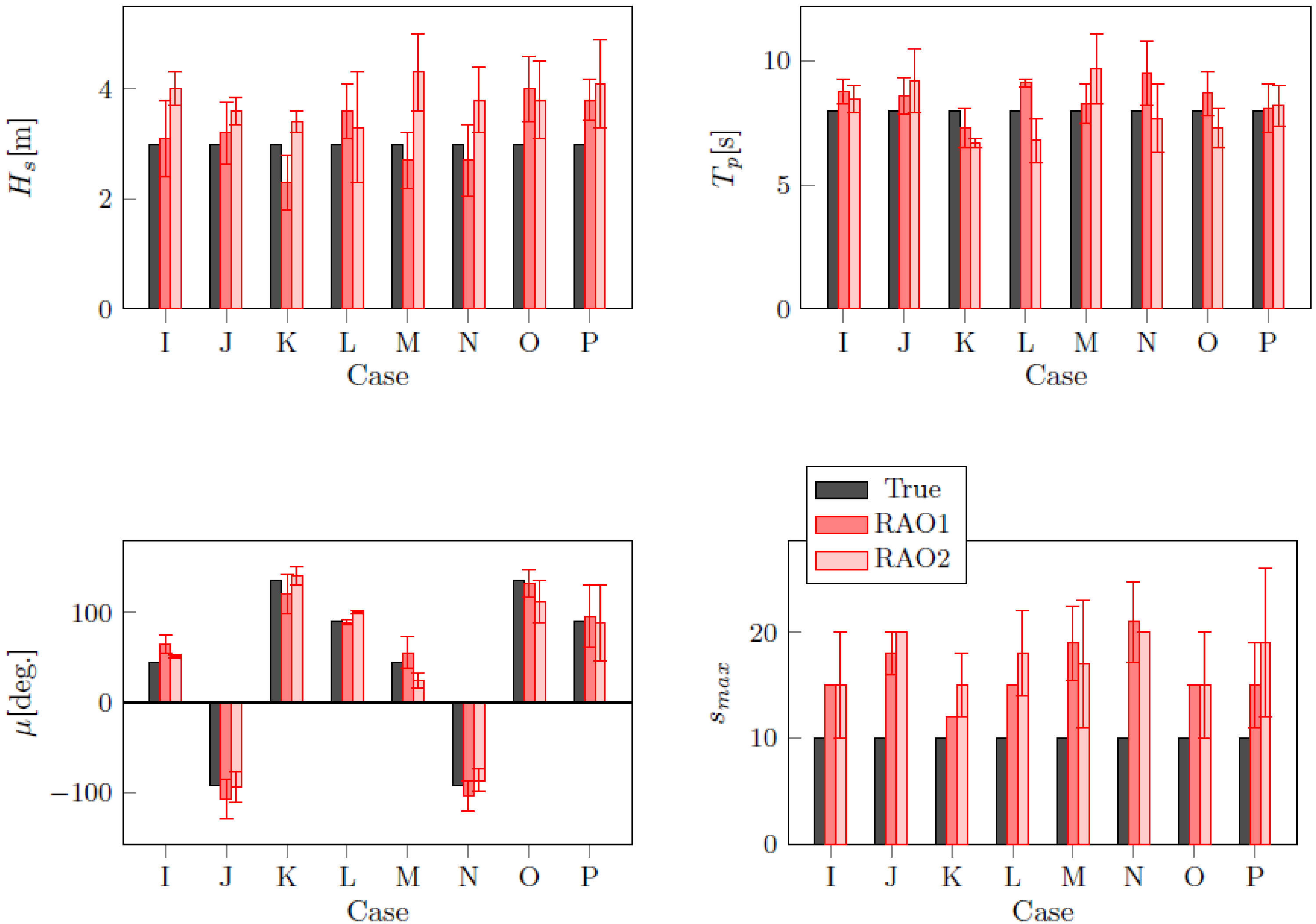
Wave estimation based on numerical simulations

Results for unimodal waves



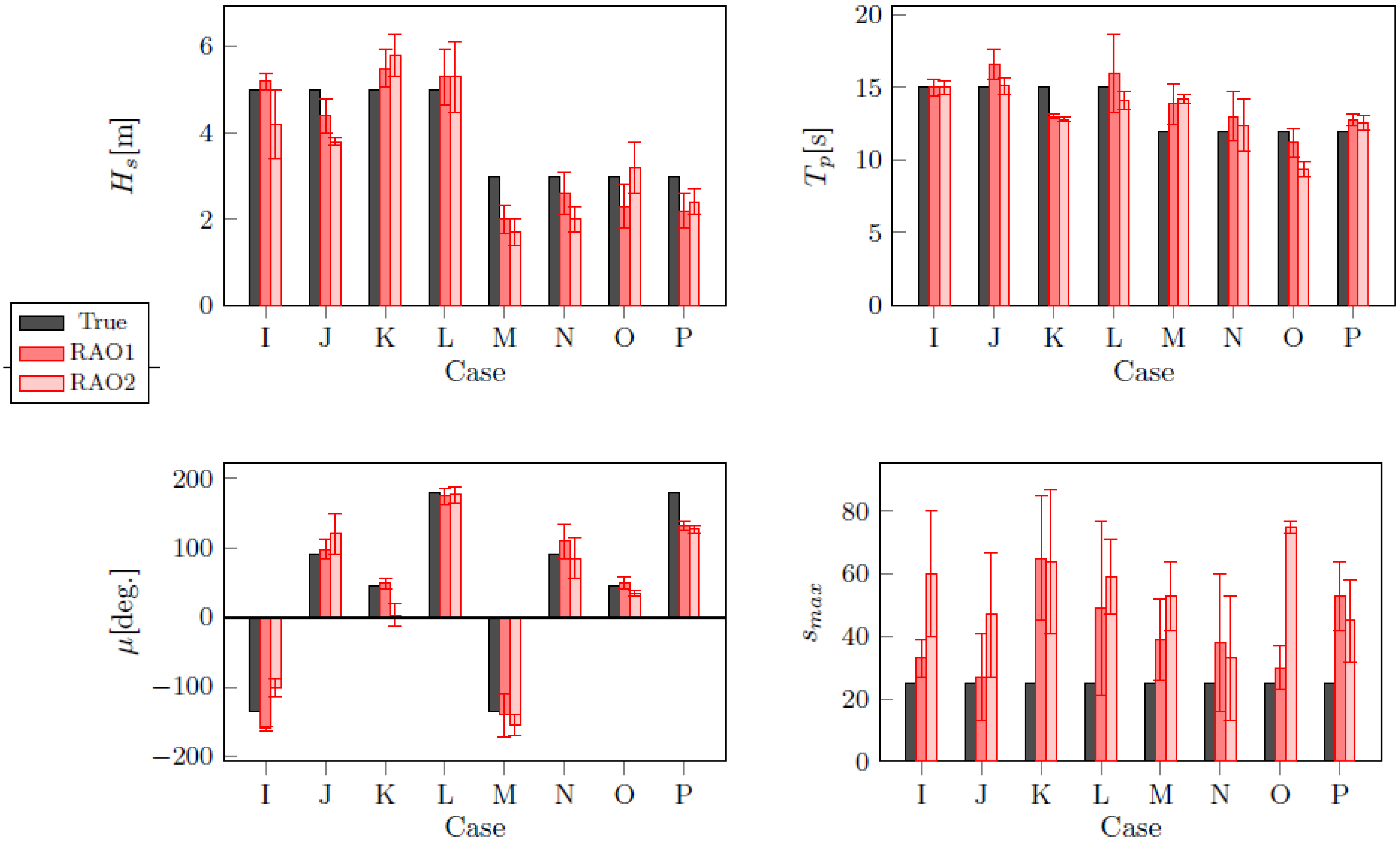
Wave estimation based on numerical simulations

Results for bimodal waves (wind part)



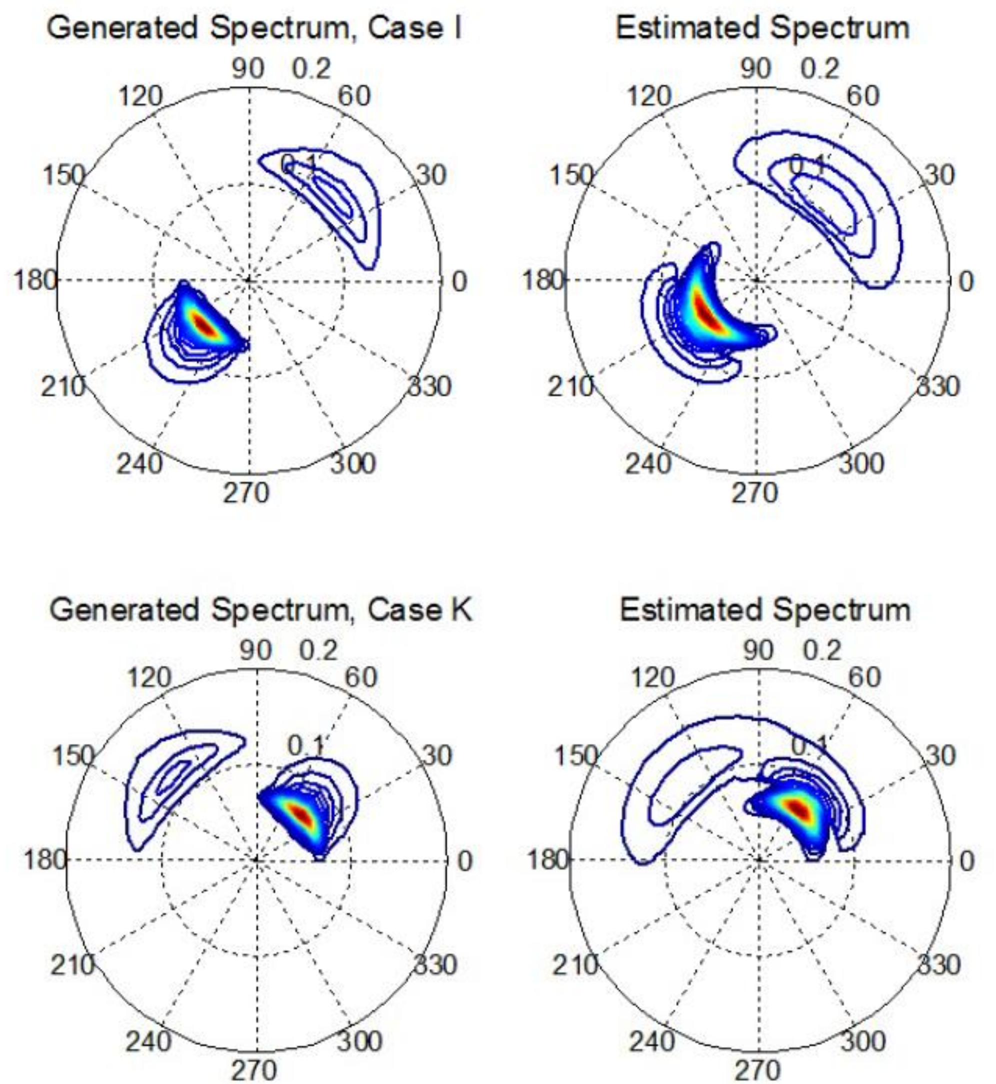
Wave estimation based on numerical simulations

Results for bimodal waves (swell part)



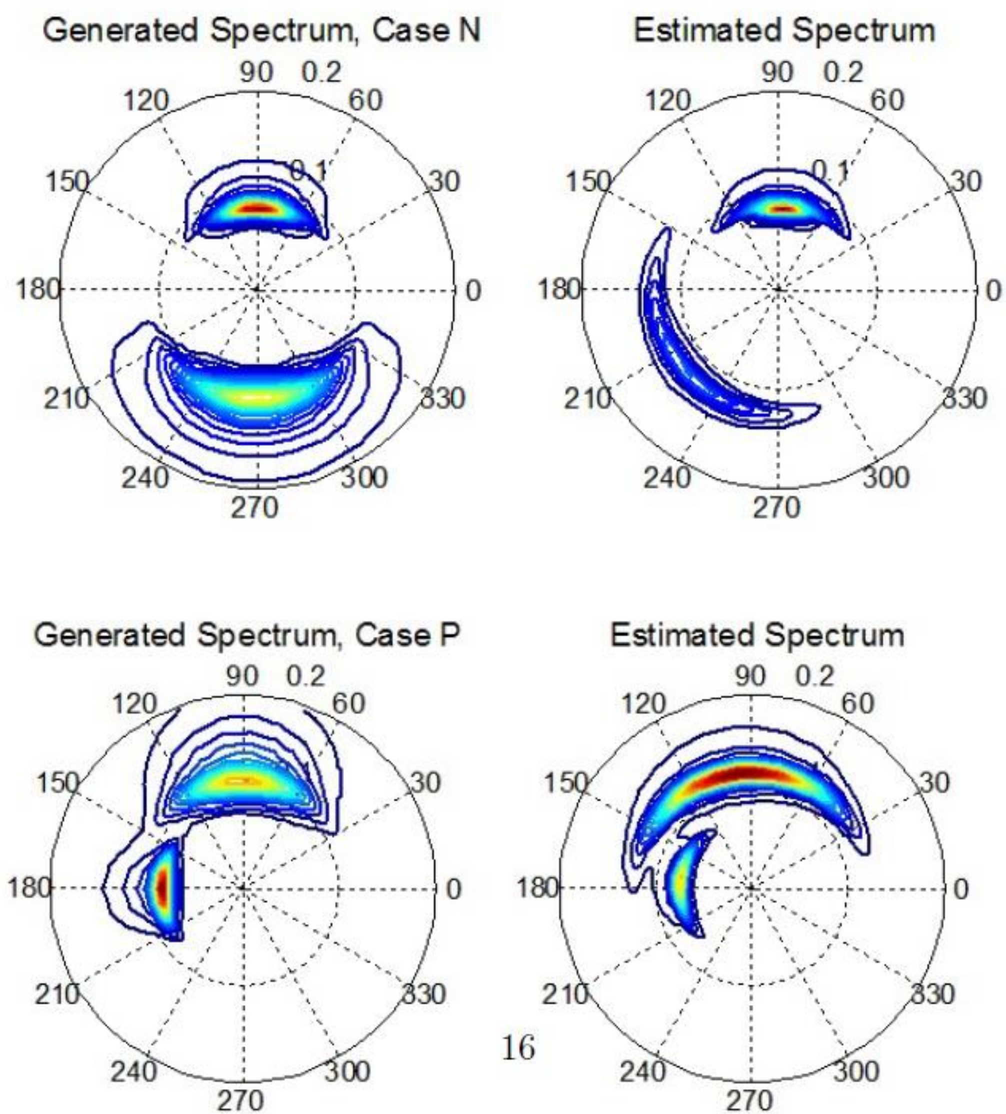
Wave estimation based on numerical simulations

Example Contour plots of estimated wave spectra



Wave estimation based on numerical simulaions

Example contour plots of estimated wave spectra



Wave estimation based on full-scale measurements

Ship No. I: 9400 TEU container ship

Ship characterisitcs:

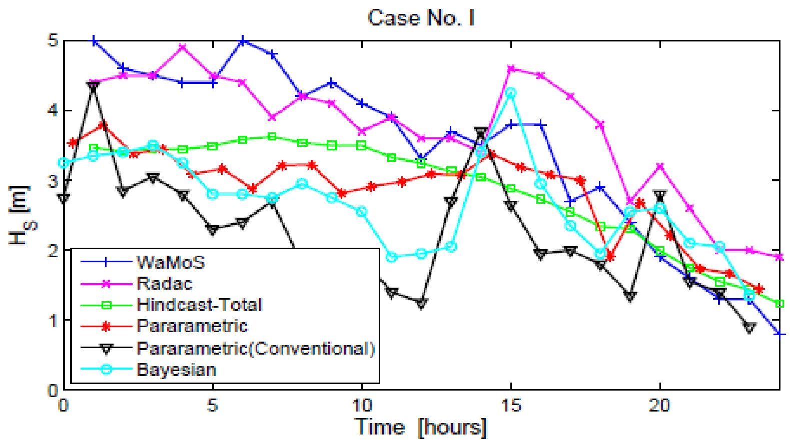
Parameter	Dimension
Overall Length	349.0 m
Beam	42.8 m
Maximum Draught	15.0 m
DWT	113,000 ton
Capacity	9415 TEU

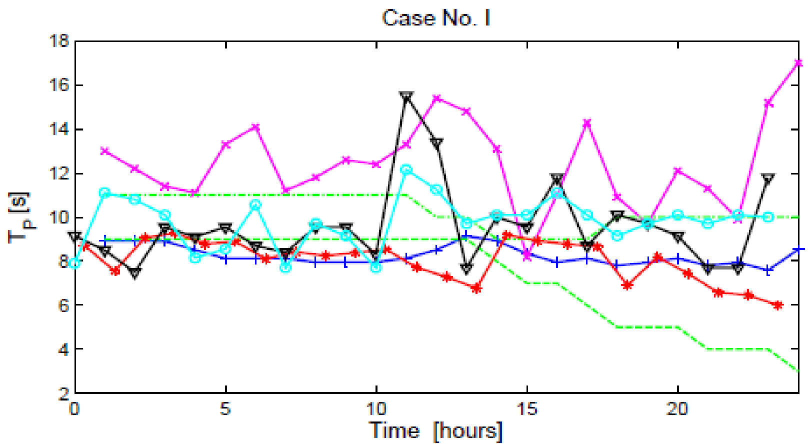
Operational conditions:

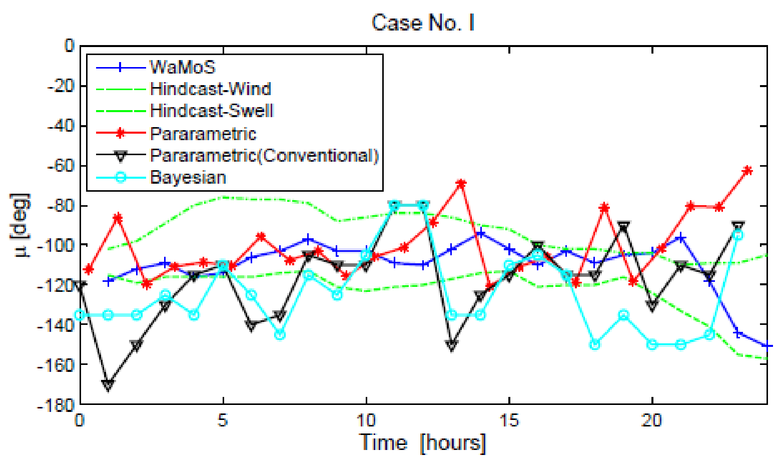
Cases	Dates	Mean Draft [m]	Speed [kn]	Location
I	12/08/2011	14.2	21.0-23.5	Gulf of Aden
II	16/09/2011	14.0	17.0-18.0	Gulf of Aden
III	20/09/2011	14.0	11.5-13.5	South of India
IV	2/10/2011	15.0	9.5-14.0	Off Hong Kong

Wave estimation based on full-scale measurements

Example results for ship No. I

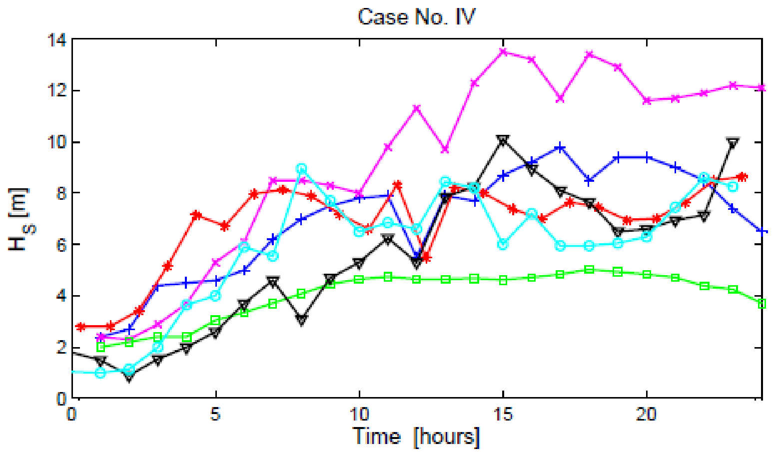


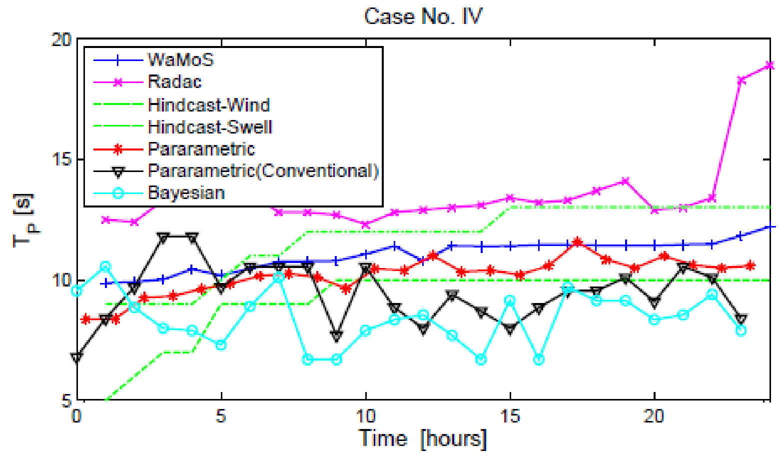


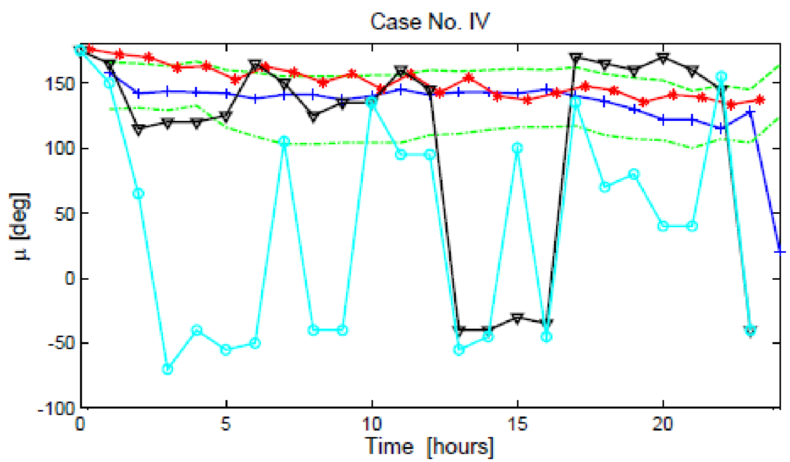


Wave estimation based on full-scale measurements

Example results for ship No. I







Wave estimation based on full-scale measurements

Ship No. II: 6800 TEU container ship

Ship characterisitcs:

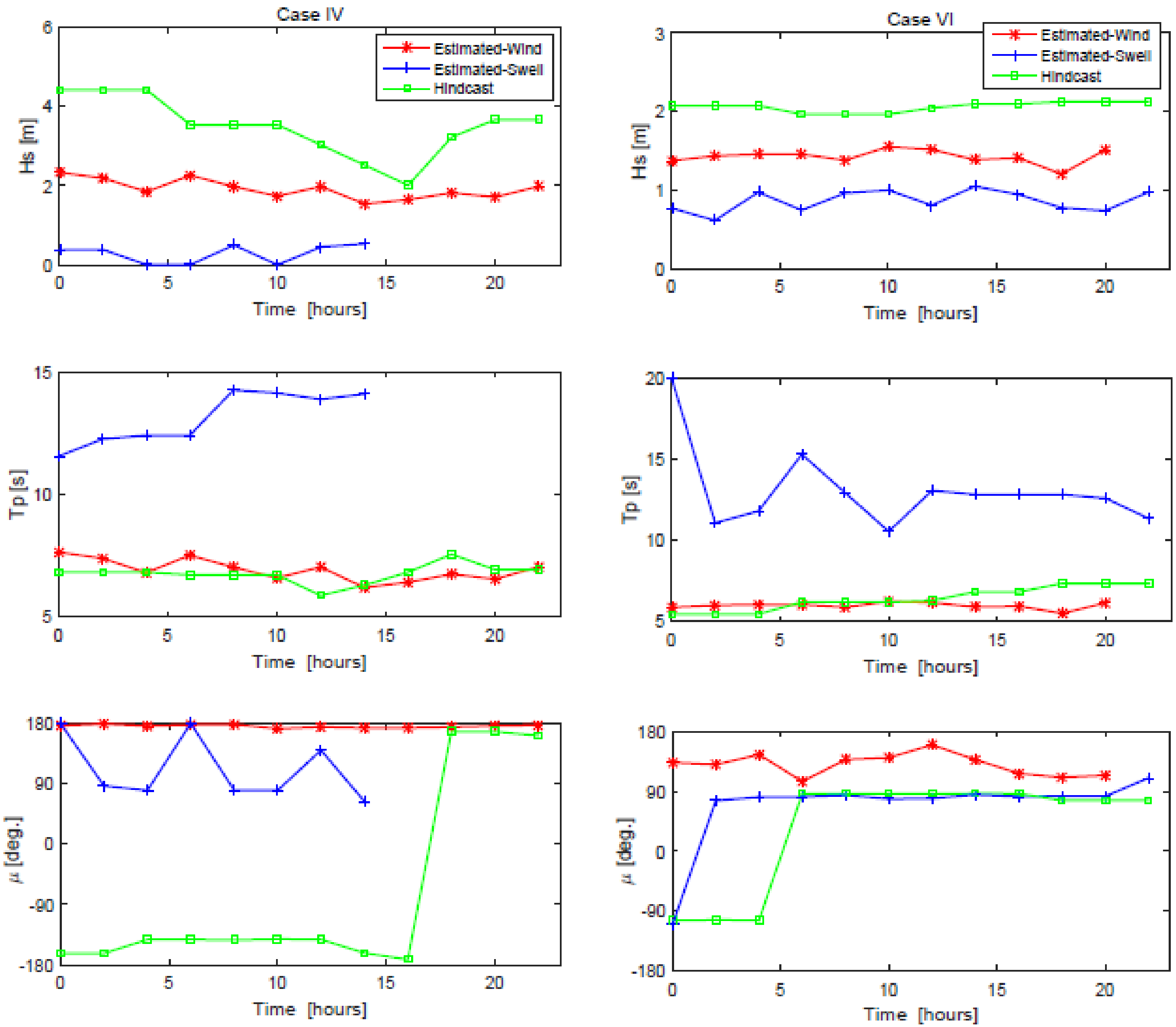
Properties	Values
Overall Length [m]	293.87
Beam [m]	40
Draught [m]	14
Maximum Speed [kn]	29
DWT [ton]	75,000

Operational conditions:

Cases	Dates	Mean Draft [m]	Average Speed [kn]	Location
I	12/08/2002	12	23	East China Sea
II	24/07/2003	11	24	Gulf of Aden
III	28/09/2003	11	21	East China Sea
IV	23/11/2003	11	22	East China Sea
V	29/11/2003	9	24	East China Sea
VI	10/01/2004	12.7	24	Arabian Sea
VII	26/05/2004	11.5	23	Arabian Sea
VIII	05/09/2004	10	20	East China Sea

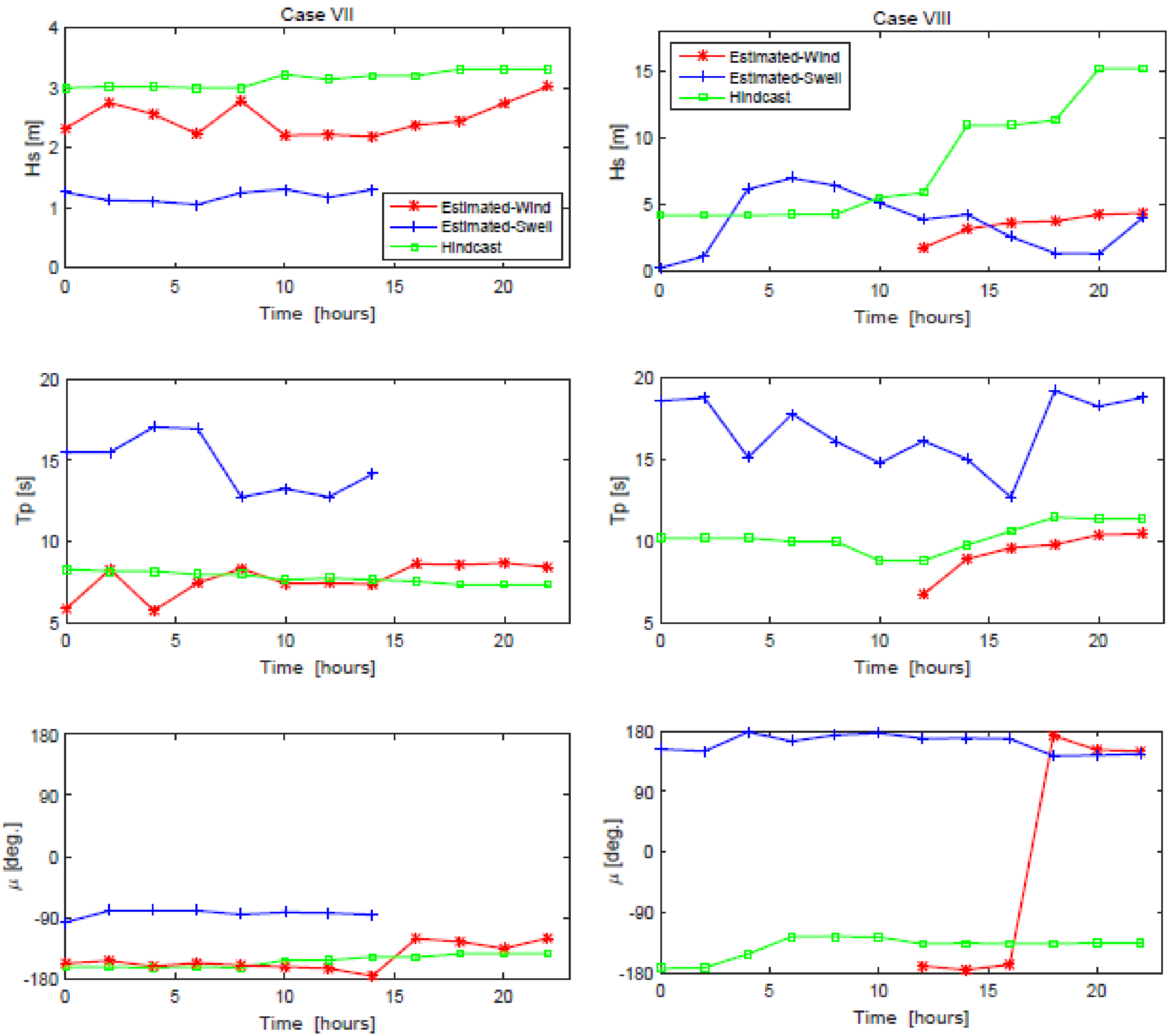
Wave estimation based on full-scale measurements

Example results for ship No. II



Wave estimation based on full-scale measurements

Example results for ship No. II



Onboard prediction of waves

Trend modelling

- Using estimations, a local regression trend model is applied to track the evolution of wave parameters during the voyage.
- Regression model:

$$Y_{N+t} = f^T(t)\boldsymbol{\theta} + \epsilon_{N+t}$$

Y_{N+t} is the wave parameter at time *N+t*

3rd order polynomial is used as $f(t) = (1, t, \frac{t^2}{2})^T$

$\boldsymbol{\theta}$ is the vector of regression parameters: $\boldsymbol{\theta} = (\theta_0, \theta_1, \theta_2)$

ϵ_{N+t} is normally distributed random variable.

$$Y_{N+t} = \theta_0 + \theta_1 t + \theta_2 \frac{t^2}{2} + \epsilon_{N+t}$$

Onboard prediction of waves

Trend modelling

- Weighted least square method is applied where the estimations in the far past are given less weight than the recent estimations. This is implemented by a forgetting factor λ.

$$SSR(\boldsymbol{\theta}; N) = \sum_{t=0}^{N-1} \lambda^t [Y_{N-t} - f^T(-t)\boldsymbol{\theta}]^2$$

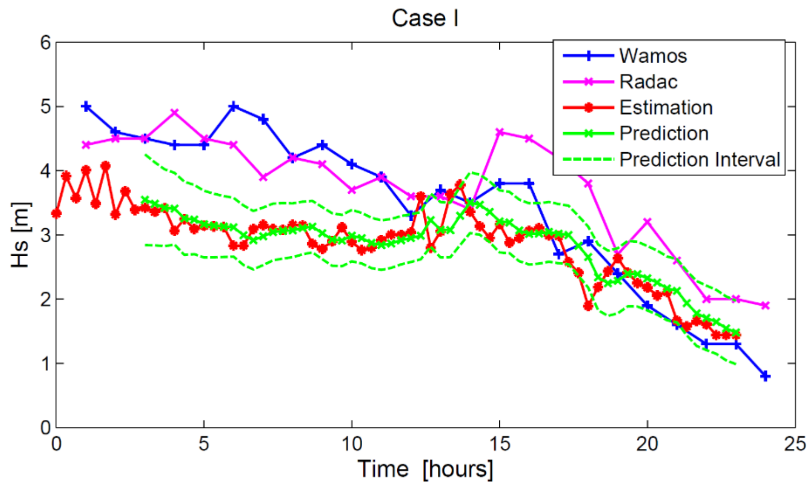
- Prediction of wave parameters in the next time step is then possible.

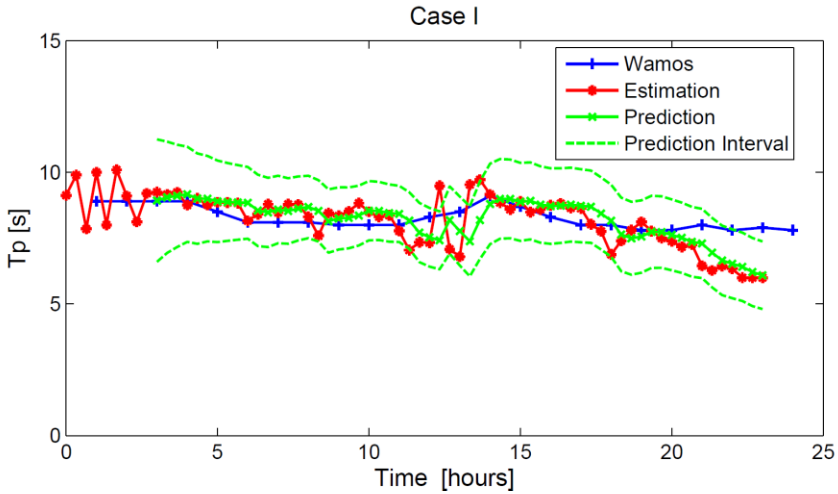
$$\widehat{Y}_{N+l|N} = f^T(l)\widehat{\boldsymbol{\theta}}_N$$

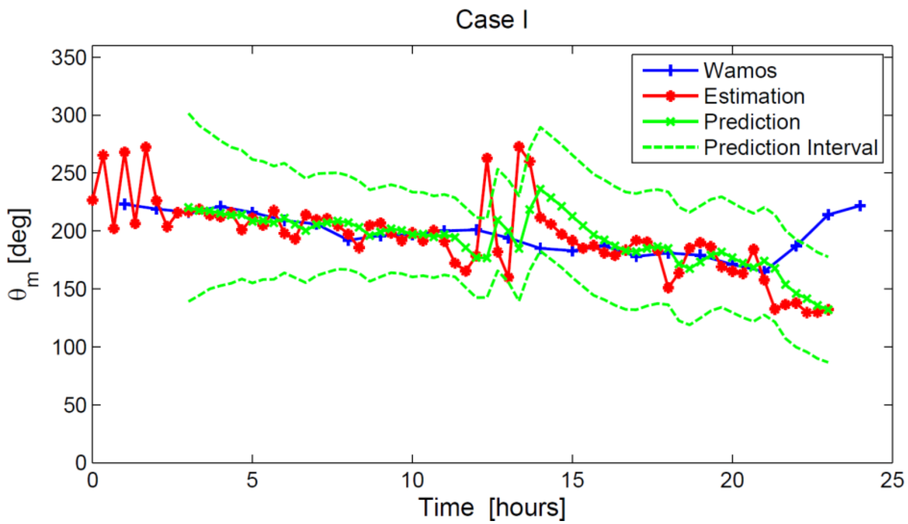
- The parameters are updated once new estimations are available.

Onboard prediction of wave parameters

Example results for ship No. I

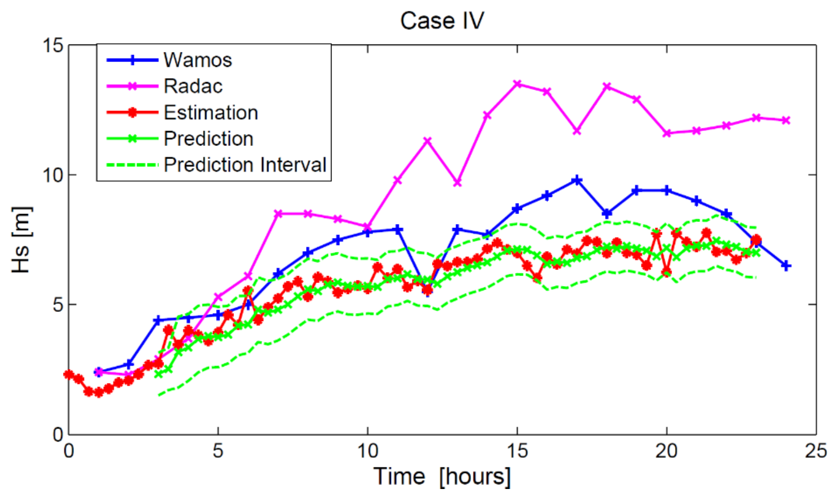


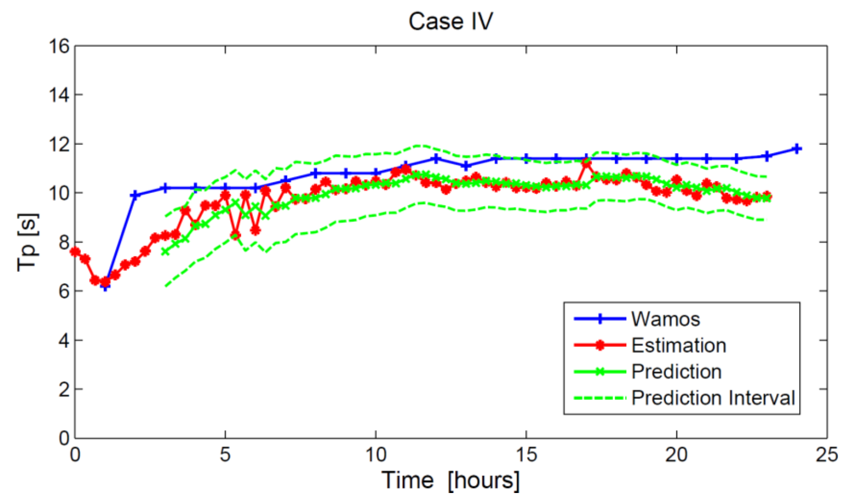


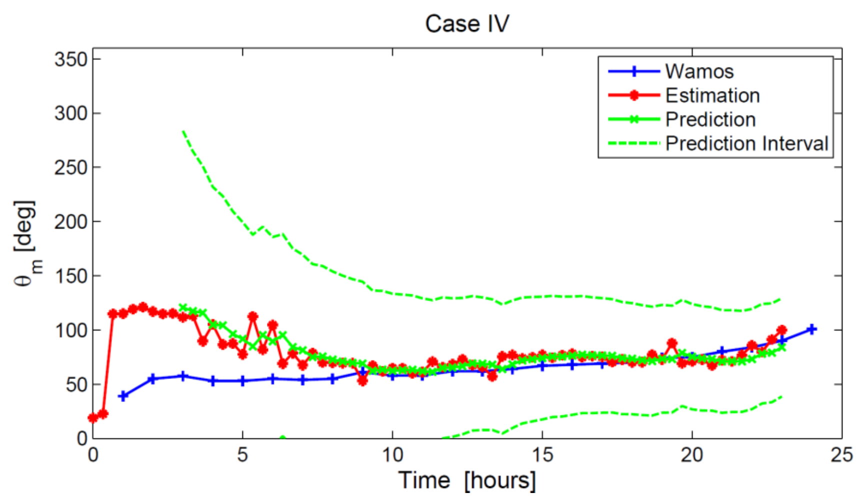


Onboard prediction of wave parameters

Example results for ship No. I







Onboard prediction of ship responses

Once, prediction of the wave parameters are available, any response can be calculated using the JONSWAP model, the new operational condition and the corresponding RAO. The variance of a response is calculated by:

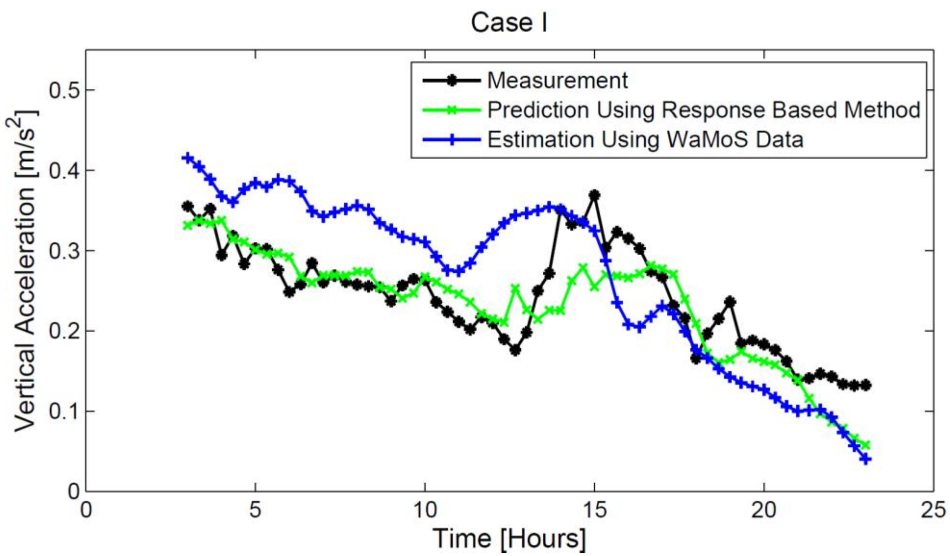
$$R_i = \int_0^\infty \int_{-\pi}^{\pi} |H_i(\omega, \theta)|^2 \, S(\omega, \theta) \, d\theta d\omega$$

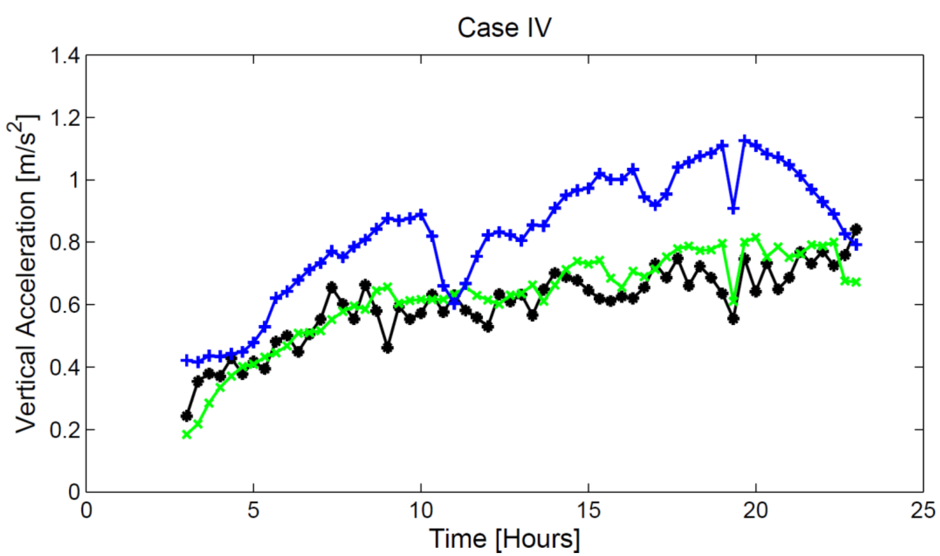
R_i : 0^{th}order spectral moment (or the variance) of the i^{th} response which represents the energy amount of that response.

Statistics of responses are usually represented by this value. Therefore, this quantity is evaluated for different responses and compared with the measurements.

Onboard prediction of ship responses

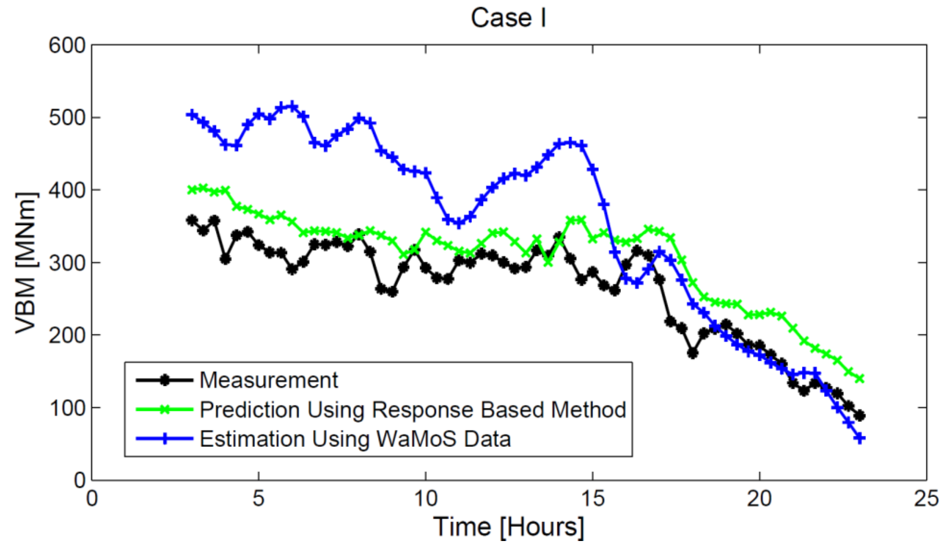
Examples for vertical acceleration

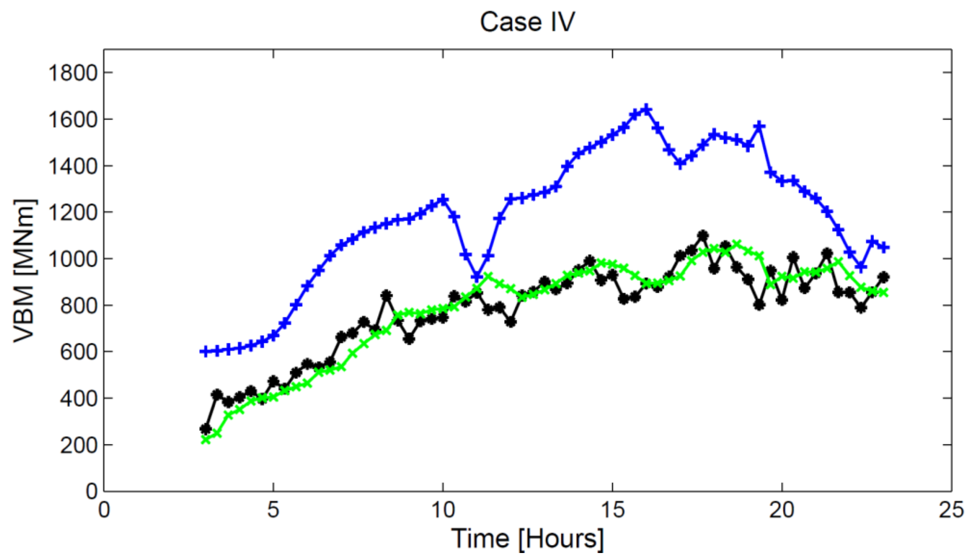




Onboard prediction of ship responses

Examples for vertical bending moment





Automatic response selection

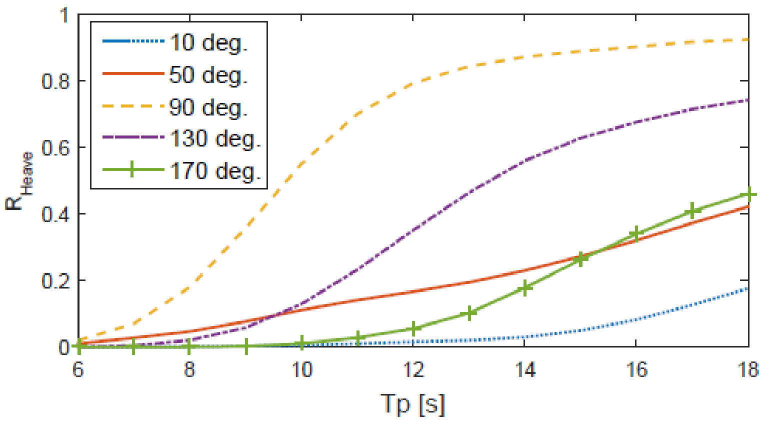
Sensitivity analysis

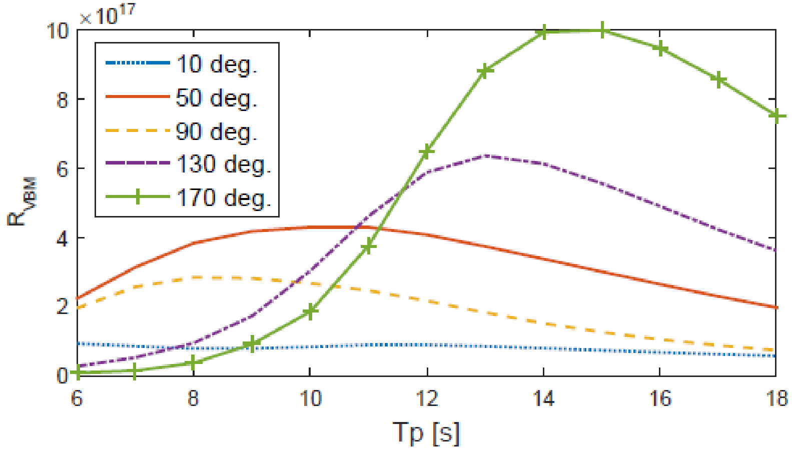
- Selection of the best combination of responses is very important. The optimum selection of responses may not be identical for all ships and all operational conditions. Therefore, this choice should be made for a particular ship in a typical operational condition.
- As shown before, the basic cost function for wave estimation is

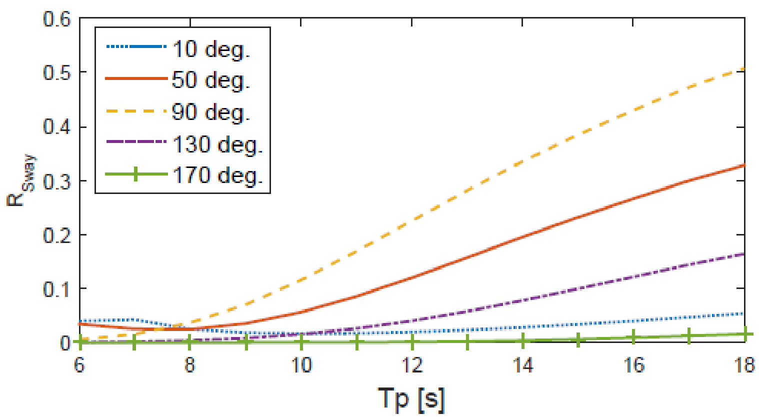
$$R_i = \int_0^\infty \int_{-\pi}^{\pi} |H_i(\omega,\theta)|^2 S(\boldsymbol{Hs}, \boldsymbol{Tp}, \boldsymbol{\mu}, \omega, \theta) d\theta d\omega \quad i = 1, \dots, n$$

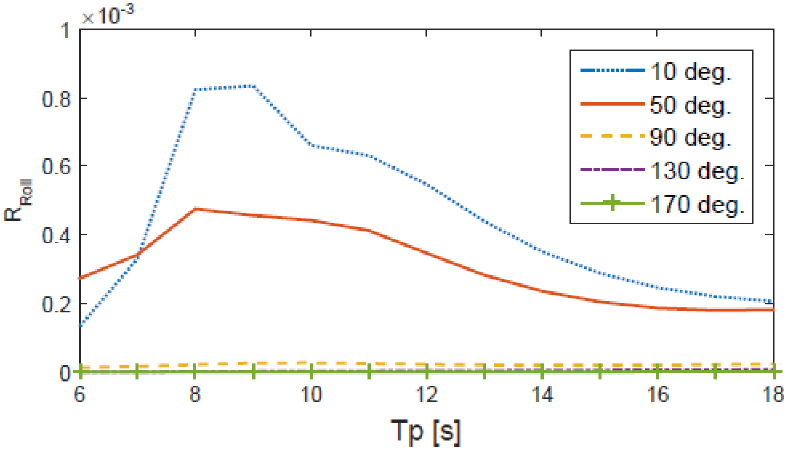
- Variability of different responses with respect to the main wave parameters can be compared.

Effect of wave parameters on individual response variances









Automatic response selection

Sensitivity analysis

- In order to decide which responses to use for wave estimation, sensitivity analysis can be implemented.

- The effect of each response variance on a specific parameter estimate can be calculated using the derivatives. A normalized sensitivity factor is defined as:

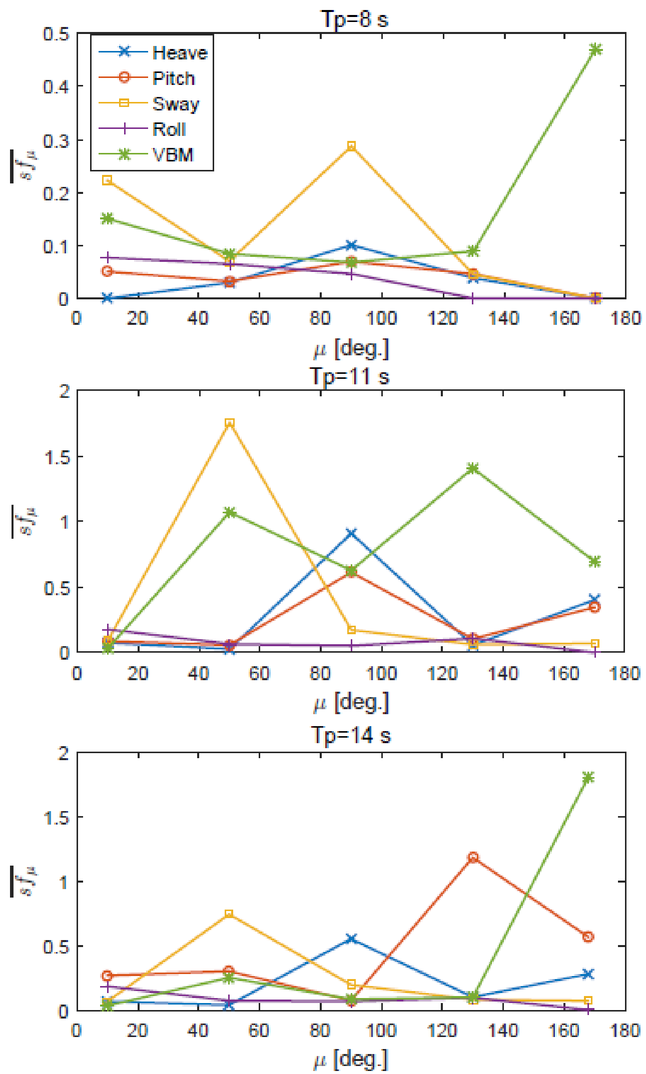
$$\overline{sf_{pj}} = \frac{\partial p}{\partial R_j} \cdot \frac{R_j}{p}$$

p: parameter ($\boldsymbol{Hs}, \boldsymbol{Tp}, \boldsymbol{\mu}$)

The derivatives are calculated using the JONSWAP model.

Automatic response selection

Example results



Summary and conclusion

- ✓ In the proposed method, the sea state is estimated using measured ship responses and a parametric wave spectrum.
- ✓ The optimization is set based on spectral moments of responses.
- ✓ The method is applied on numerical data and full scale measurements of in-service container ships.
- ✓ Comparisons are made between the current method and the previous methods in the literature.
- ✓ The results show that the method is efficient and promising.
- ✓ A local regression trend model is proposed for onboard prediction of sea state parameters.
- ✓ The trend model provides a smooth and consistent evolution of wave parameters.
- ✓ The predictions are then used to estimate the responses of the ship in 20 minutes.
- ✓ The prediction results show a good agreement with the actual measurements.
- ✓ The procedure can be applied onboard ships to provide the actual safe and risky areas in terms of different ship speeds and courses.
- ✓ This information can be shown as polar plots.

Future works

- Consider a wide set of wave scenarios numerically to exract the limiting wave characteristics that can be estimated by the current method.
- Consider Larger ships e.g. 18000 TEU container ships as case study to see if the method is still efficient for wave estimation.
- Improving initializations and constraints of the optimization by using e.g. hindcast data and trend analysis.
- The proposed local sensitivity analysis in this thesis can be employed to select the response combination in specific sea sates. The results should be compared with the originals.
- More full-scale tests/experiments are required to validate the robustness of wave buoy analogy in general.
- Further studies are recommended to do a comparative evaluation of the different methods.
- Ways to combine the parametric moment-based method with other methods, e.g. Bayesian method can be proposed to improve the efficiency of wave buoy analogy.
- Uncertainty evaluation of all methods should be developed.

Thank you!