SPRAI: Seakeeping prediction using artificial intelligence

Pablo Romero Tello
Naval Technology Area. Applied physics and Naval technology department
Escuela Técnica Superior de Ingeniería Naval y Oceánica
Universidad Politécnica de Cartagena (UPCT)
E-mail: pablo.romero@upct.es

José Enrique Gutiérrez Romero
Naval Technology Area. Applied physics and Naval technology department
Escuela Técnica Superior de Ingeniería Naval y Oceánica
Universidad Politécnica de Cartagena (UPCT)
E-mail: jose.gutierrez@upct.es

Borja Serván Camas
Centre Internacional de Metodes Numerics en Enginyeria (CIMNE)
E-mail: bservan@cimne.upc.edu

Antonio J. Lorente López
Naval Technology Area. Applied physics and Naval technology department
Escuela Técnica Superior de Ingeniería Naval y Oceánica
Universidad Politécnica de Cartagena (UPCT)
E-mail: antonioj.lorente@upct.es

EUROPEAN UNIVERSITY OF TECHNOLOGY
"Think human first"

TRANSFORMANDO LOS OCÉANOS:
INNOVACIÓN e ingeniería naval para un mundo CONECTADO y SOSTENIBLE

CIIN 2024
63°

CIMNE
EXCELENCIA SEVERO OCHOA

General Index

I. Introduction and objectives

In the field of Naval Architecture, the application of AI can be of considerable relevance.

This study presents the development of the SPRAI tool, based on AI algorithms, which allows the assessment of the **seakeeping** of a ship, with very **short pre-processing and calculation times**. The AI will determine the added masses, damping and external forces required to calculate the seakeeping of conventional monohull vessels.

$$\left(M + A_{ij}\right)\ddot{\eta}_j + B_{ij}\dot{\eta}_j + K_{ij}\eta_j = F_j \cdot e^{-i\omega t}$$

I. Introduction and objectives

The methodology used for the generation of the SPRAI tool is described. This tool is capable of predicting the seakeeping of monohull vessels in displacement condition.

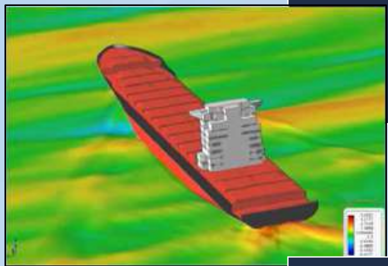
- The **error** made by the SPRAI must be **acceptable**.
- The **inference time** has to be **very short**.
- It must be able to solve the diffraction radiation problem in **early design stages**.

II. Methodology

Base ship geometries

Augmentation of the ship database

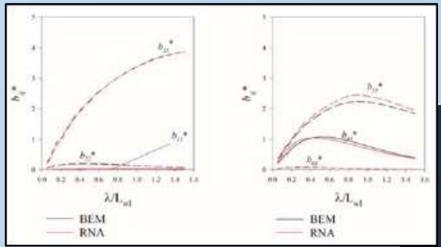
Simulation



Generation of databases

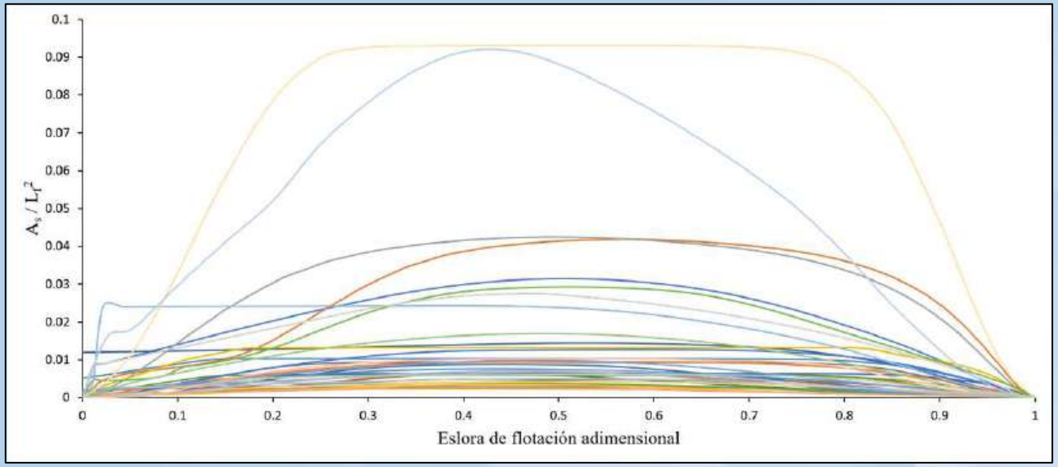
Training ANN

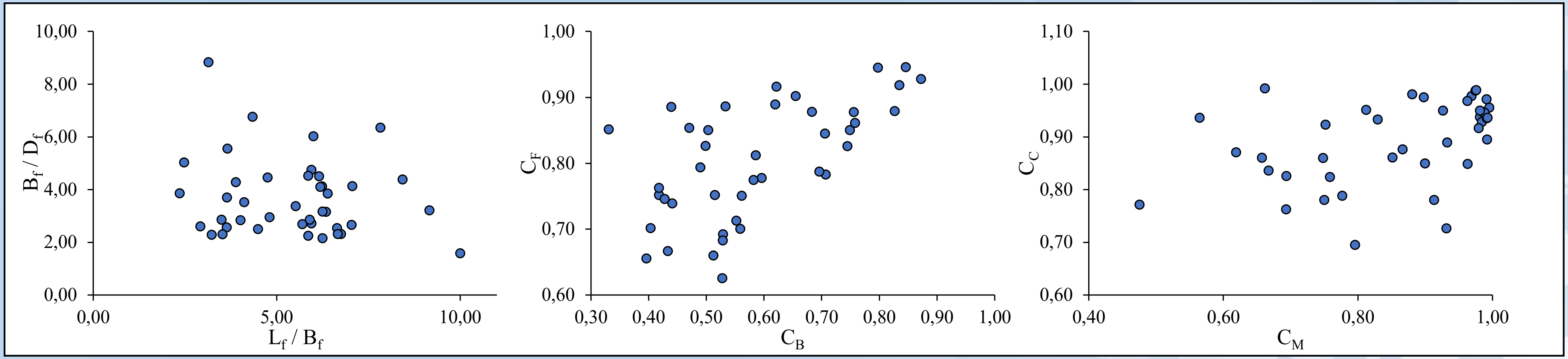
Evaluation



III. Data sets Generation: Base ships

60 Base ships





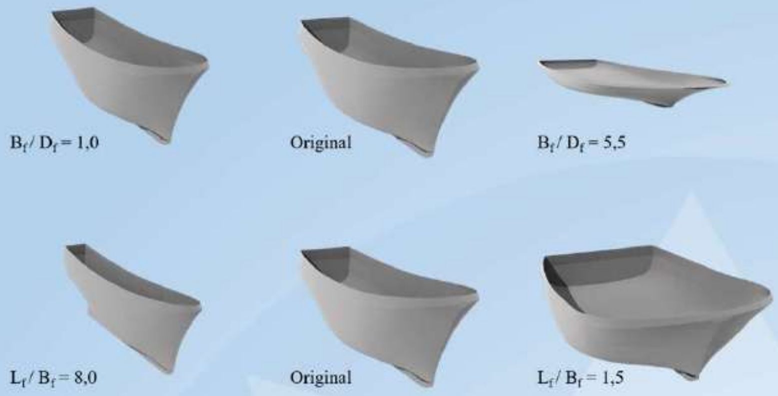
III. Data sets Generation: Data Augmentation

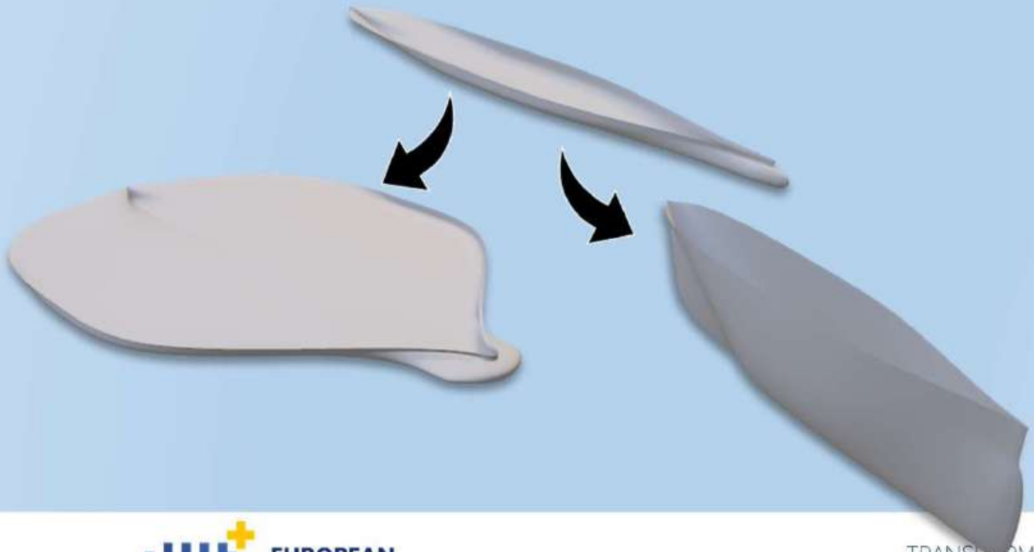
Parametric transformation:

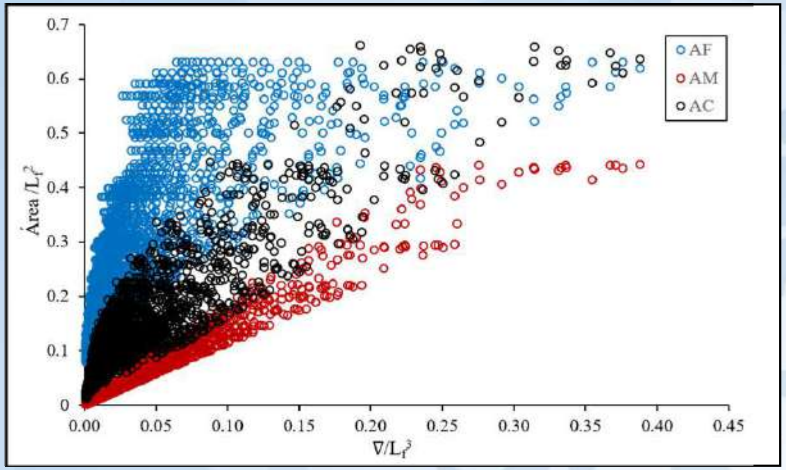
$$1{,}5 \leq \frac{L_f}{B_f} \geq 8{,}0$$

$$1{,}0 \leq \frac{B_f}{D_f} \geq 5{,}5$$

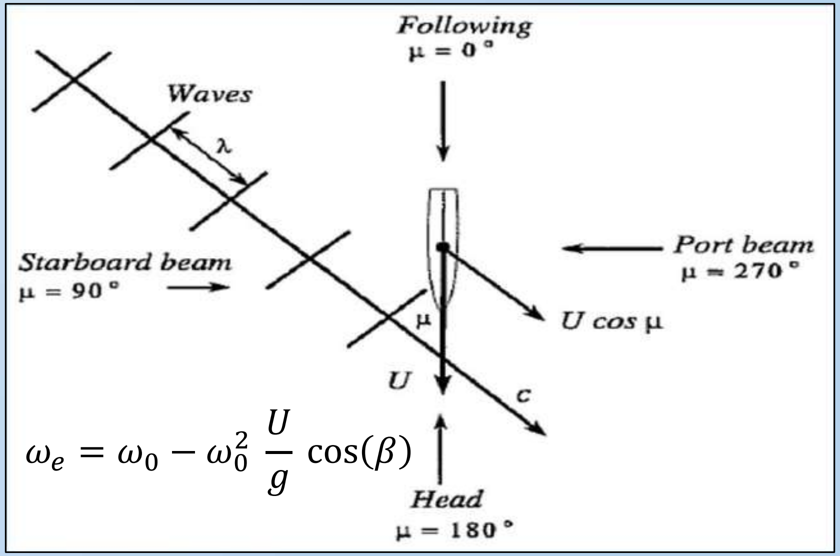
- 100 Cases per base ship
- 6.000 Cases







III. Data sets Generation: Encounter Frequency



$$\omega_e = \omega_0 - \omega_0^2 \frac{U}{g} \cos(\beta)$$

$$[A] = \begin{pmatrix} A_{11} & 0 & A_{13} & 0 & A_{15} & 0 \\ 0 & A_{22} & 0 & A_{24} & 0 & A_{26} \\ A_{31} & 0 & A_{33} & 0 & A_{35} & 0 \\ 0 & A_{42} & 0 & A_{44} & 0 & A_{46} \\ A_{51} & 0 & A_{53} & 0 & A_{55} & 0 \\ 0 & A_{62} & 0 & A_{64} & 0 & A_{66} \end{pmatrix}$$

Hypothesis

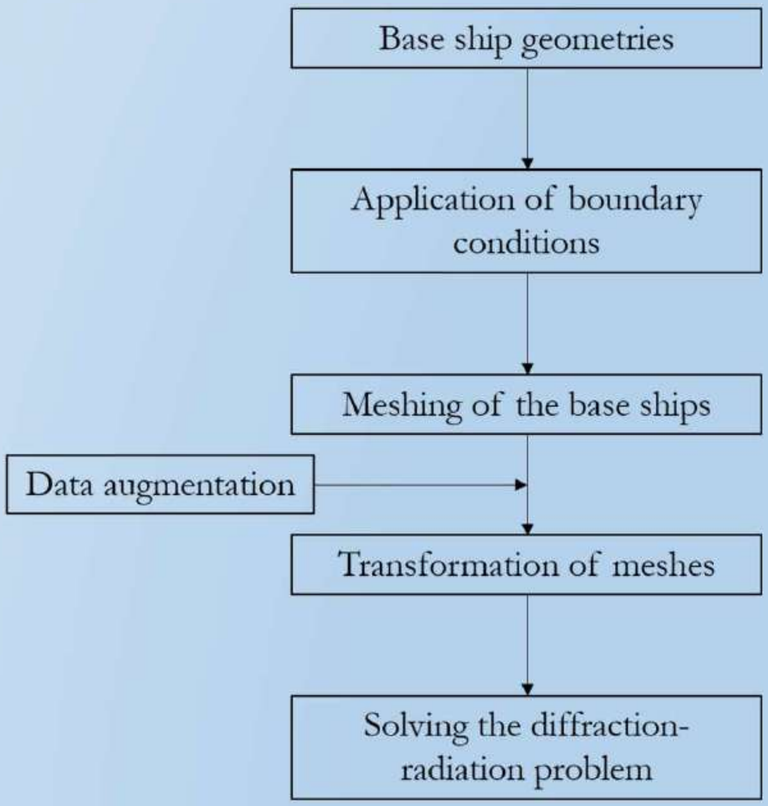
- ❑ The flow is considered potential.
- ❑ The wave amplitude is small.
- ❑ A linear relationship between wave amplitude and ship motion is considered.
- ❑ The ship is a rigid solid.

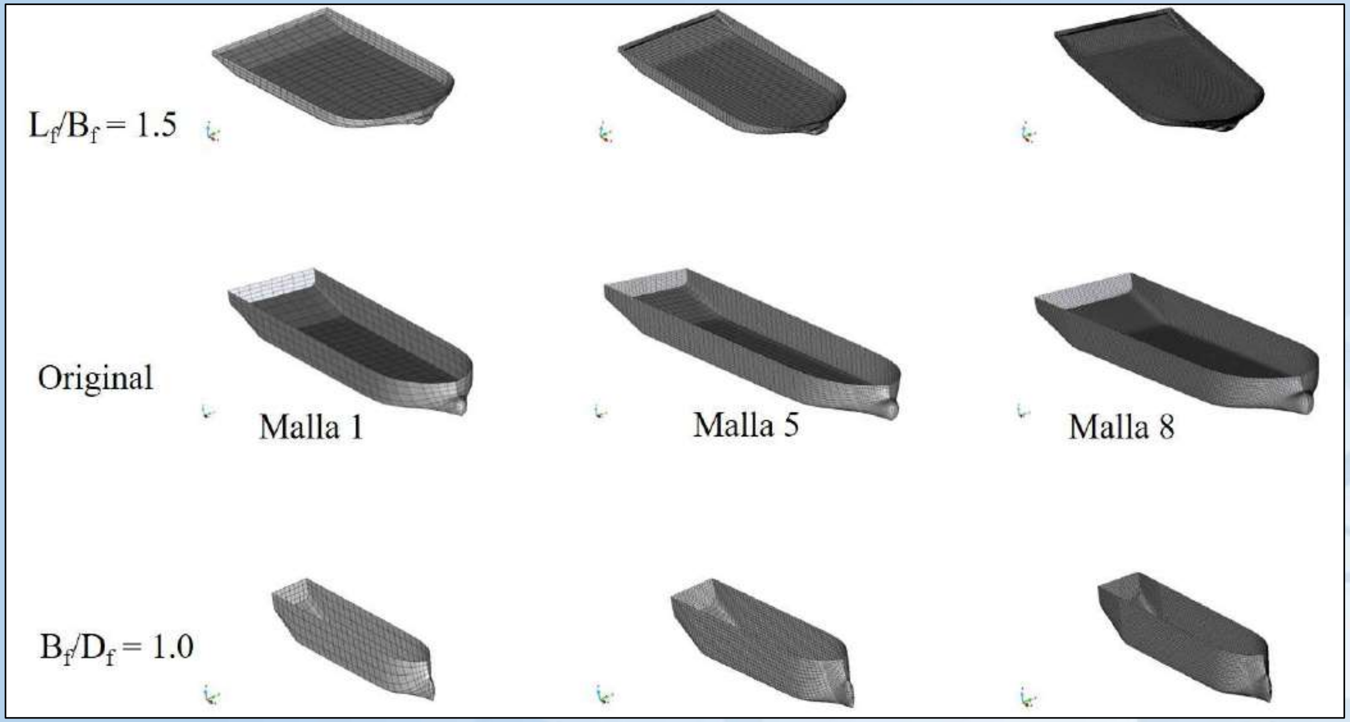
Resolución del problema

- ❑ The BEM method is used in the frequency domain.

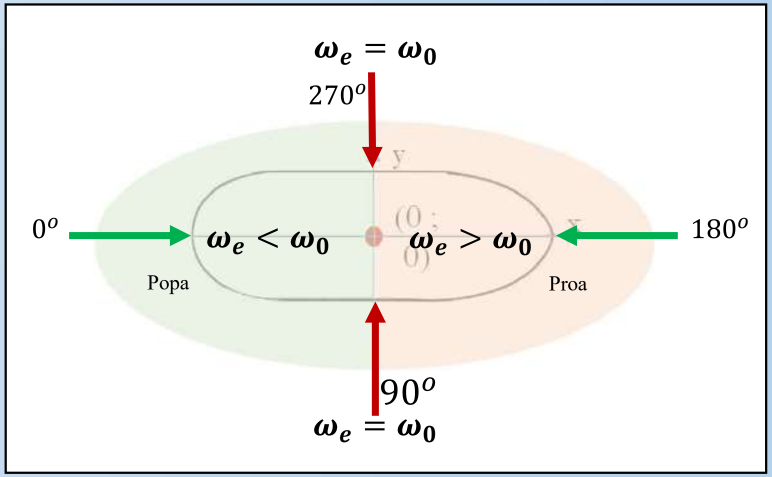
$$[B] = \begin{pmatrix} B_{11} & 0 & B_{13} & 0 & B_{15} & 0 \\ 0 & B_{22} & 0 & B_{24} & 0 & B_{26} \\ B_{31} & 0 & B_{33} & 0 & B_{35} & 0 \\ 0 & B_{42} & 0 & B_{44} & 0 & B_{46} \\ B_{51} & 0 & B_{53} & 0 & B_{55} & 0 \\ 0 & B_{62} & 0 & B_{64} & 0 & B_{66} \end{pmatrix}$$

III. Data sets Generation: Mesh Transformation





III. Data sets Generation: Simulation



- Dimensionless: $L_f = 1\ m$
- 12 Wave heading: $[0 \leq \beta \geq \pi]$
- 14 Wave lengths: $\left[\frac{L_f}{5} \geq \lambda \leq 3L_f\right]$
- 7 Speeds: $[0{,}025 \geq Fn \leq 0{,}30]$

1.365 ω_e per *Ship* **($5{,}6 \times 10^6$)**

The diffraction-radiation problem is solved. BEM code.

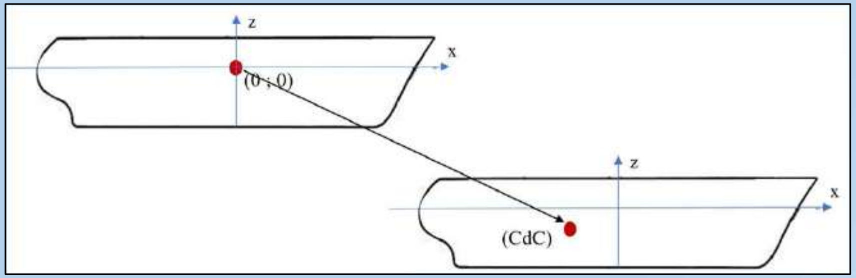
$A_{ij}; B_{ij}; F_{Dif}; F_{FK}; \delta_{Dif}; \delta_{FK}$

- Inputs ➔ The main dimensions and form coefficients
- Targets ➔ Added mass and damping matrices and excitation forces

$$\left(A_{ij}\,;\, B_{ij}\,;\, F_{Dif}\,;\, F_{FK}\,;\, \delta_{Dif};\delta_{FK}\right) = f\left(Fn, \omega_0, \beta, \frac{B_f}{L_f}, \frac{D_f}{L_f}, C_b, C_f, C_m, C_c, \frac{X_B}{L_f}, \frac{Z_B}{D_f}\right)$$

III. Data sets Generation: Data processing

- **Traslado**: origin of coordinates (BEM) ➔ C.d.C. (training)



- **Normalisation** of databases

$$\begin{cases} \bar{\bar{M}}\,\ddot{x} + \overline{\overline{A_{xx}}}\,\ddot{x} + \overline{\overline{A_{x\theta}}}\,\ddot{\theta} + \overline{\overline{B_{xx}}}\,\dot{x} + \overline{\overline{B_{x\theta}}}\,\dot{\theta} + \overline{\overline{C_{xx}}}\,x + \overline{\overline{C_{x\theta}}}\,\theta = f \\ \bar{\bar{I}}\,\ddot{\theta} + \overline{\overline{A_{\theta x}}}\,\ddot{x} + \overline{\overline{A_{\theta\theta}}}\,\ddot{\theta} + \overline{\overline{B_{\theta x}}}\,\dot{x} + \overline{\overline{B_{\theta\theta}}}\,\dot{\theta} + \overline{\overline{C_{\theta x}}}\,x + \overline{\overline{C_{\theta\theta}}}\,\theta = m \end{cases}$$

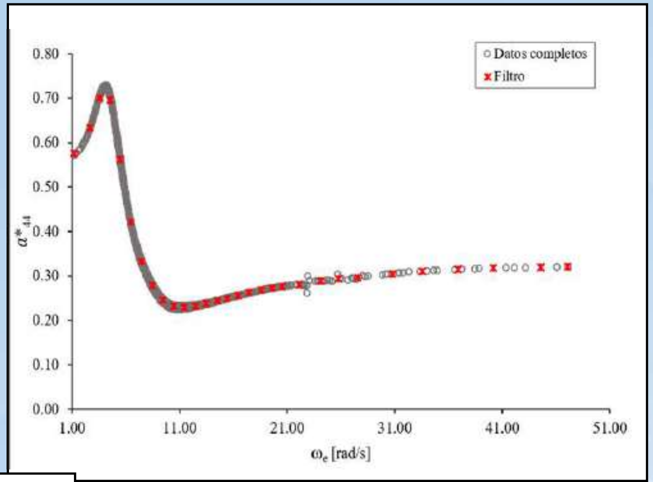
$$\begin{cases} x \sim O(\xi) & \theta \sim O(\xi k) \\ \dot{x} \sim O(\xi\omega) & \dot{\theta} \sim O(\xi k\omega) \\ \ddot{x} \sim O(\xi\omega^2) & \ddot{\theta} \sim O(\xi k\omega^2) \end{cases}$$

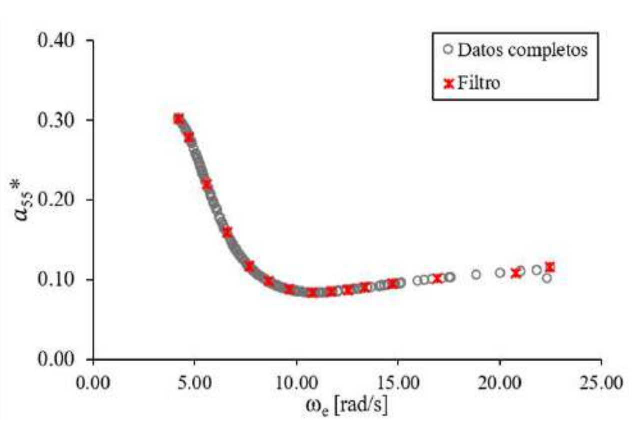
$$\begin{cases} 1 + \dfrac{a_{xx}}{\nabla\,\rho} + \dfrac{a_{x\theta}}{\nabla\,\rho}\mathrm{k}_{ref} + \dfrac{b_{xx}}{\nabla\,\rho\,\omega_e} + \dfrac{b_{x\theta}}{\nabla\,\rho\,\omega_e}k_{ref} + \dfrac{c_{xx}}{\nabla\,\rho\,\omega_{ref}} + \dfrac{c_{xx}}{\nabla\,\rho\,\omega_{ref}}k_{ref} = \dfrac{f}{\nabla\,\rho\xi\,\omega_{ref}^2} \\ 1 + \dfrac{a_{\theta x}}{I\,k_{ref}} + \dfrac{a_{\theta\theta}}{I} + \dfrac{b_{\theta x}}{I\,k_{ref}\,\omega_e} + \dfrac{b_{\theta\theta}}{I\,\omega_e} + \dfrac{c_{\theta x}}{I\,\omega_{ref}} + \dfrac{c_{\theta\theta}}{I\,gk_{ref}^2} = \dfrac{m}{I\,\xi\,\omega_{ref}^2\,k} \end{cases}$$

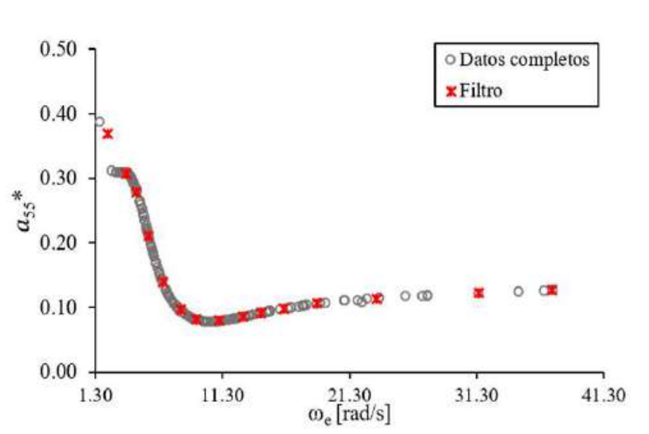
$$k_{ref} = \frac{2\pi}{L_f} \quad \omega_{ref} = \sqrt{g\,\frac{2\pi}{L_f}}$$

III. Data sets Generation: Data Filtering

- Added Mass and Damping
- 1.365 points of ω_e
- Not affected by the Fn → a curve with 1.365 points
- Affected by the Fn → 7 curves with 195 points
- 1.365 → 31 points of ω_e
- 195 → 15 points of ω_e







EUROPEAN UNIVERSITY OF TECHNOLOGY
"Think human first"

TRANSFORMANDO LOS OCÉANOS: INNOVACIÓN e ingeniería naval para un mundo CONECTADO y SOSTENIBLE

CIIN 2024 63° Congreso Internacional de Ingeniería Naval e Industria Marítima

CIMNE EXCELENCIA SEVERO OCHOA

III. Data sets Generation: Data Sets

INPUT

Fn, ω_0, $\frac{B_f}{L_f}$, $\frac{D_f}{L_f}$, C_b, C_f, C_m, $\frac{X_B}{L_f}$, $\frac{Z_B}{D_f}$

TARGET

$f_{x\,0^o}, f_{x\,30^o}, f_{x\,60^o}$
$f_{x\,90^o}$
$f_{x\,120^o}, f_{x\,150^o}, f_{x\,180^o}$
$f_{y\,30^o}, f_{y\,60^o}, f_{y\,90^o}, f_{y\,120^o}, f_{y\,150^o}$
$f_{z\,0^o}, f_{z\,30^o}, f_{z\,60^o}, f_{z\,90^o}, f_{z\,120^o}, f_{z\,150^o}, f_{z\,180^o}$
$m_{x\,30^o}, m_{x\,60^o}$
$m_{x\,90^o}$
$m_{x\,120^o}, m_{x\,150^o}$
$m_{y\,0^o}, m_{y\,30^o}, m_{y\,60^o}$
$m_{y\,90^o}$
$m_{y\,120^o}, m_{y\,150^o}, m_{y\,180^o}$
$m_{z\,30^o}, m_{z\,60^o}, m_{z\,90^o}, m_{z\,120^o}, m_{z\,150^o}$

INPUT

$\omega_e, \frac{B_f}{L_f}, \frac{D_f}{L_f}, C_b, C_f, C_m, \frac{X_B}{L_f}, \frac{Z_B}{D_f}$
$\omega_e, \frac{B_f}{L_f}, \frac{D_f}{L_f}, C_b, C_f, C_m, C_c, \frac{X_B}{L_f}, \frac{Z_B}{D_f}$
$Fn, \omega_e, \frac{B_f}{L_f}, \frac{D_f}{L_f}, C_b, C_f, C_m, \frac{X_B}{L_f}, \frac{Z_B}{D_f}$
$Fn, \omega_e, \frac{B_f}{L_f}, \frac{D_f}{L_f}, C_b, C_f, C_m, C_c, \frac{X_B}{L_f}, \frac{Z_B}{D_f}$
$Fn, \omega_e, \frac{B_f}{L_f}, \frac{D_f}{L_f}, C_b, C_m, C_c, \frac{X_B}{L_f}, \frac{Z_B}{D_f}$

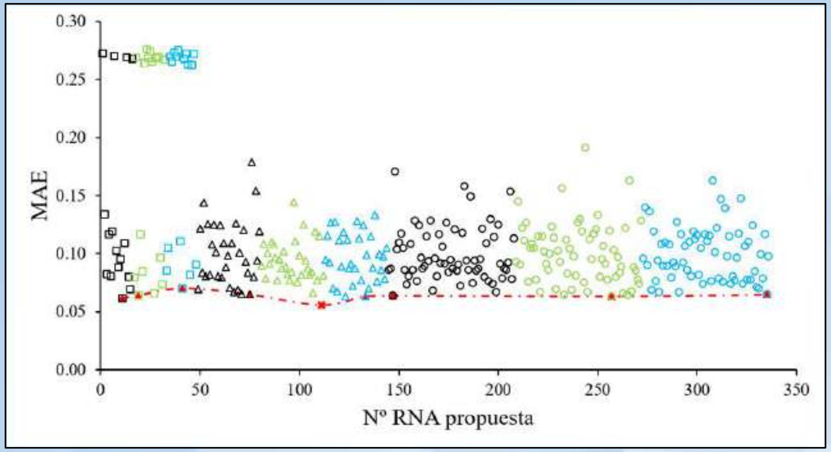
TARGET

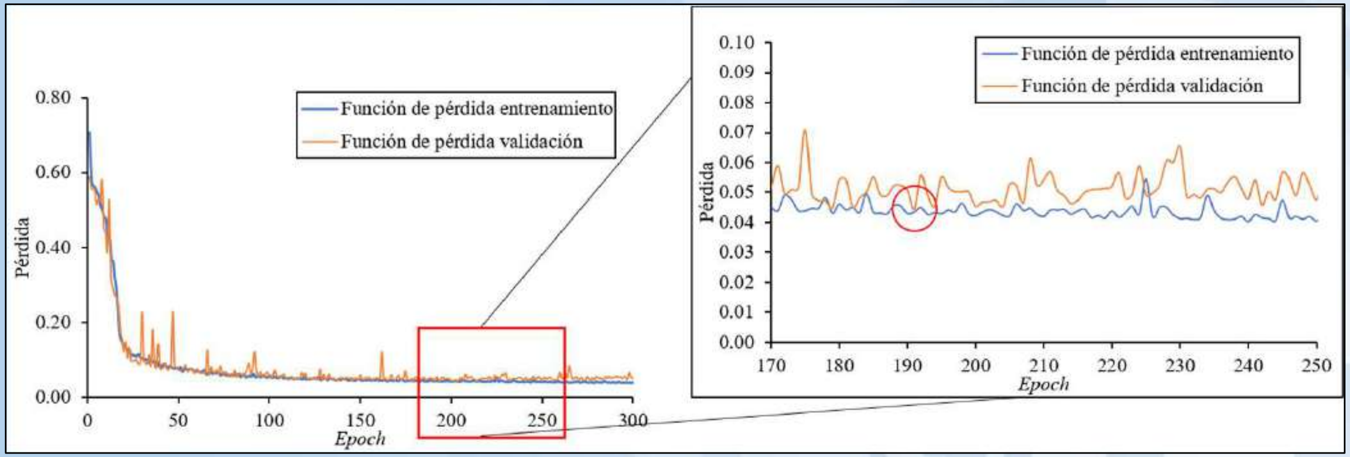
$[a^*_{11}, a^*_{13}, a^*_{31}]$
$[a^*_{22}, a^*_{24}, a^*_{33}, a^*_{42}, a^*_{44}]$
$[a^*_{15}], [a^*_{35}], [a^*_{51}], [a^*_{53}], [a^*_{55}]$
$[a^*_{46}], [a^*_{64}]$
$[a^*_{26}], [a^*_{62}], [a^*_{66}]$
$[b^*_{11}, b^*_{13}, b^*_{31}, b^*_{22}, b^*_{24}, b^*_{33}, b^*_{42}, b^*_{44}]$
$[b^*_{15}], [b^*_{35}], [b^*_{51}], [b^*_{53}], [b^*_{55}]$
$[b^*_{46}], [b^*_{64}]$
$[b^*_{26}], [b^*_{62}], [b^*_{66}]$

IV. Training

- 70% training, 15% validation y 15% test
- MPL on Keras together with Tensorflow GPU-Nvidia
- *Model Checkpoint* → *Overfitting*

Capas	3 – 4 – 5
Neuronas	30 – 40 – 50
Optimizadores	Adam, RMSprop
Funciones de activación	Sigmoid, ReLU
Máx. *Epoch*	300
Loss function	MAE





EUROPEAN UNIVERSITY OF TECHNOLOGY
"Think human first"

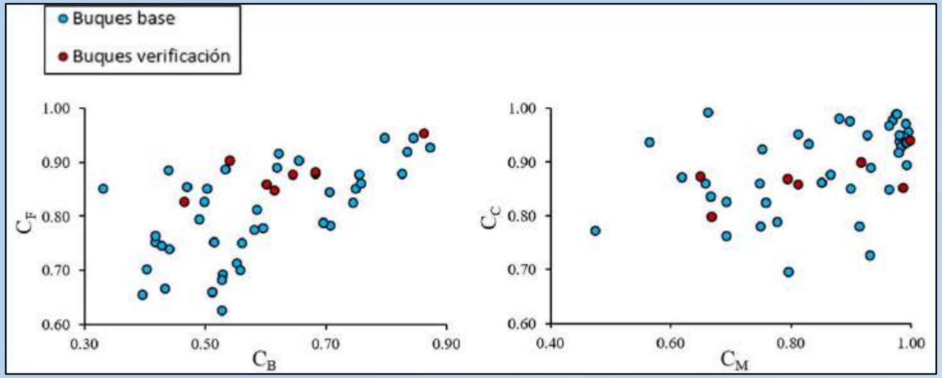
TRANSFORMANDO LOS OCÉANOS: INNOVACIÓN e ingeniería naval para un mundo CONECTADO y SOSTENIBLE

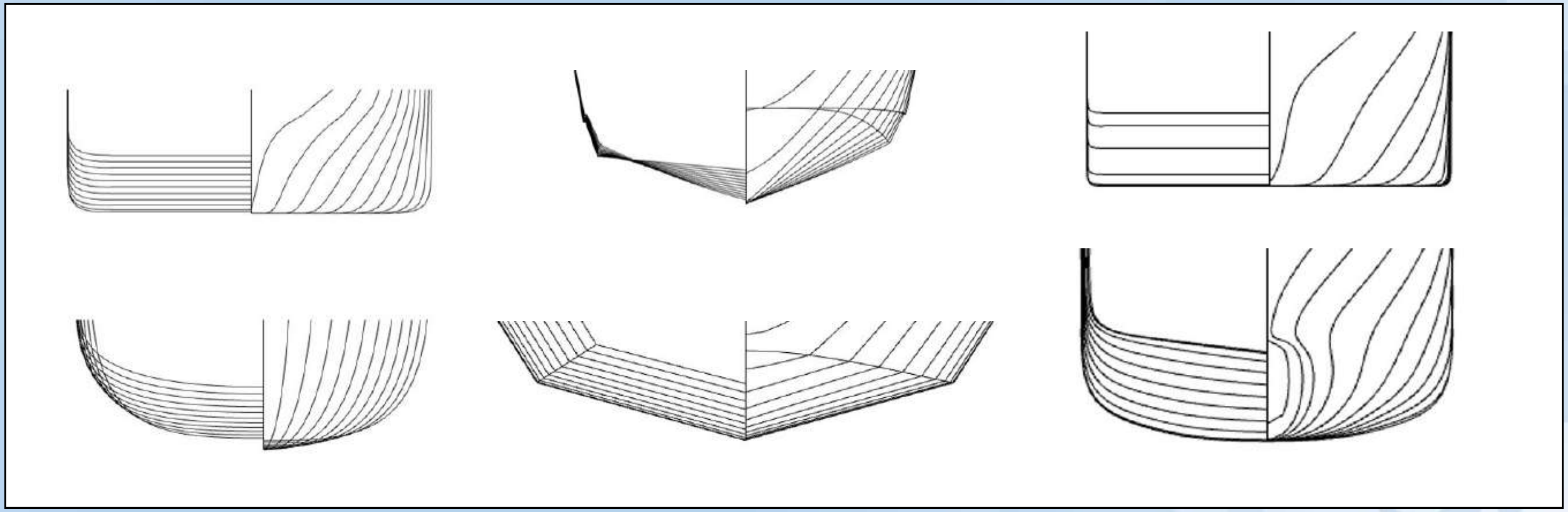
CIIN 2024 63º

CIMNE EXCELENCIA SEVERO OCHOA

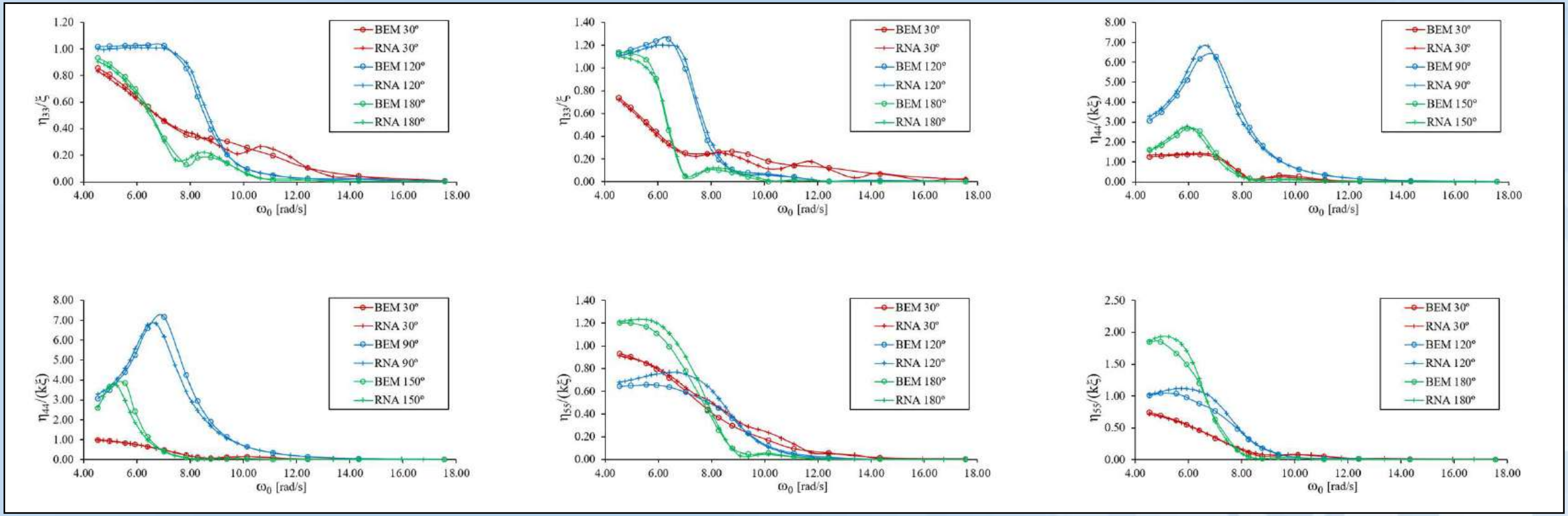
V. Results

- General cargo
- Practical
- FPSO
- Sailing ship
- Work Vessel
- Yacht

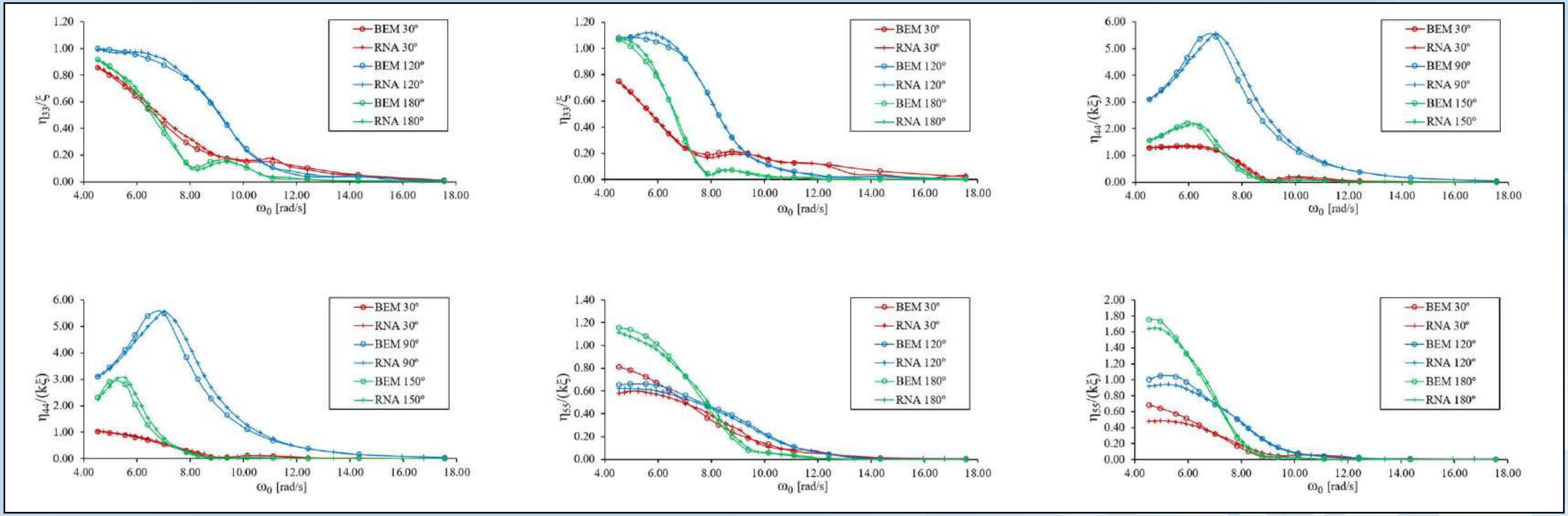




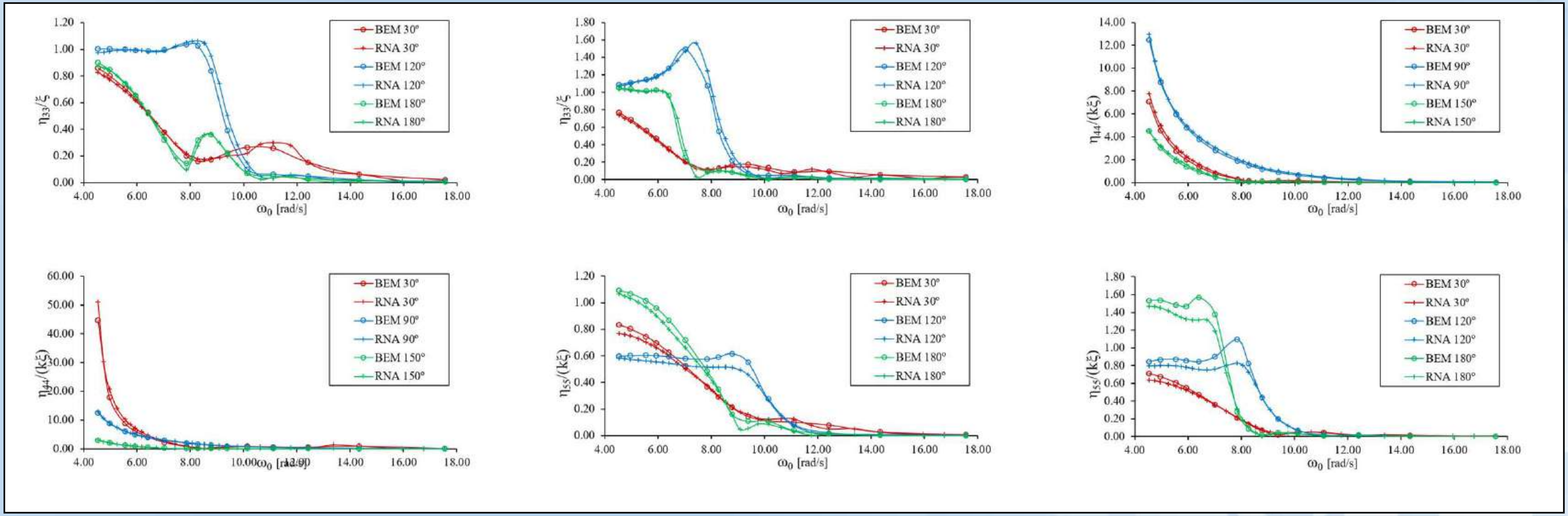
V. Results: General cargo



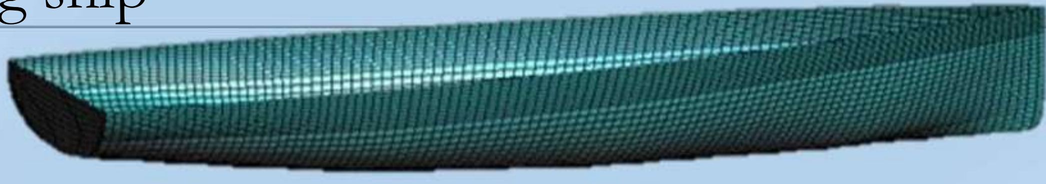
V. Results: Practical

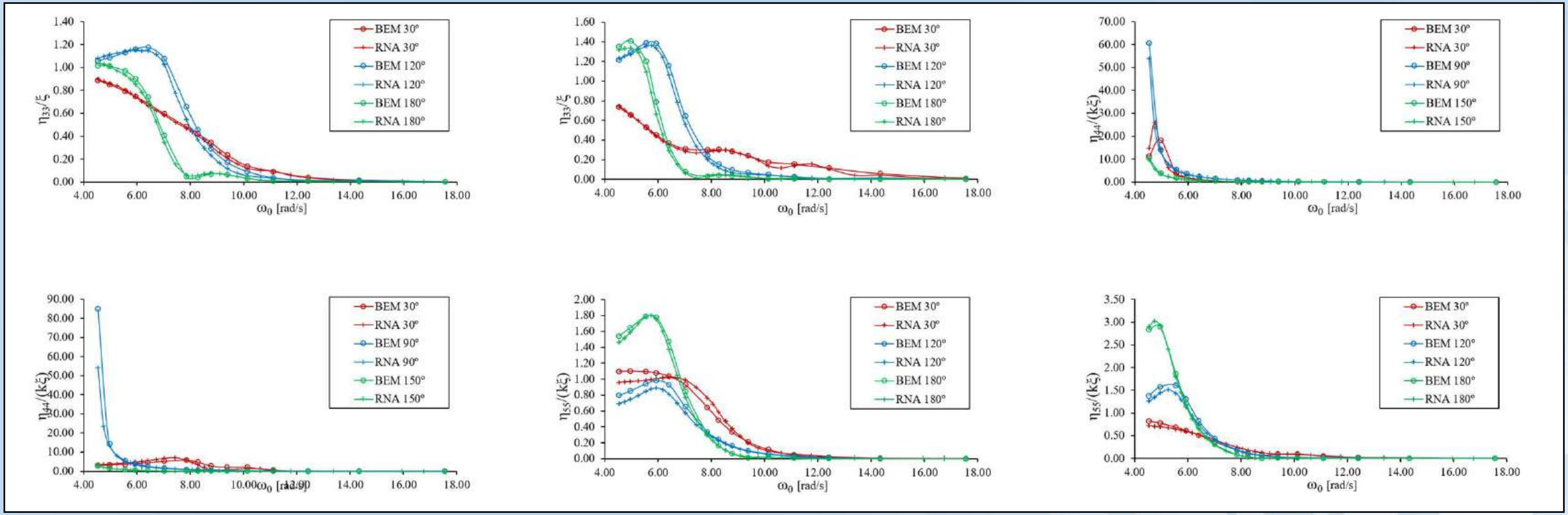


V. Results: FPSO



V. Results: Sailing ship





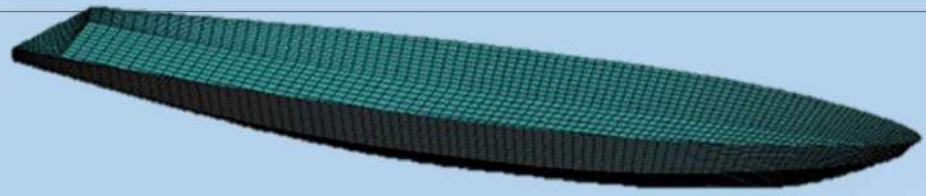
TRANSFORMANDO LOS OCÉANOS: INNOVACIÓN e ingeniería naval para un mundo CONECTADO y SOSTENIBLE

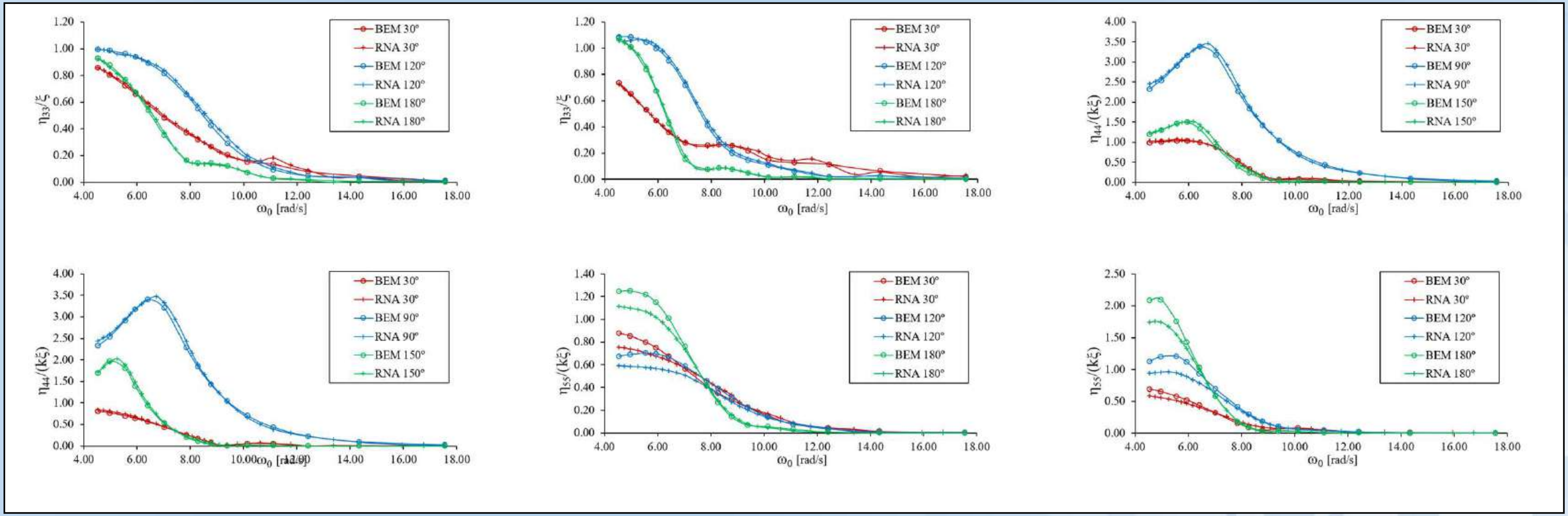
CIIN 2024

EUROPEAN UNIVERSITY OF TECHNOLOGY
"Think human first"

CIMNE
EXCELENCIA SEVERO OCHOA

V. Results: Work Vessel





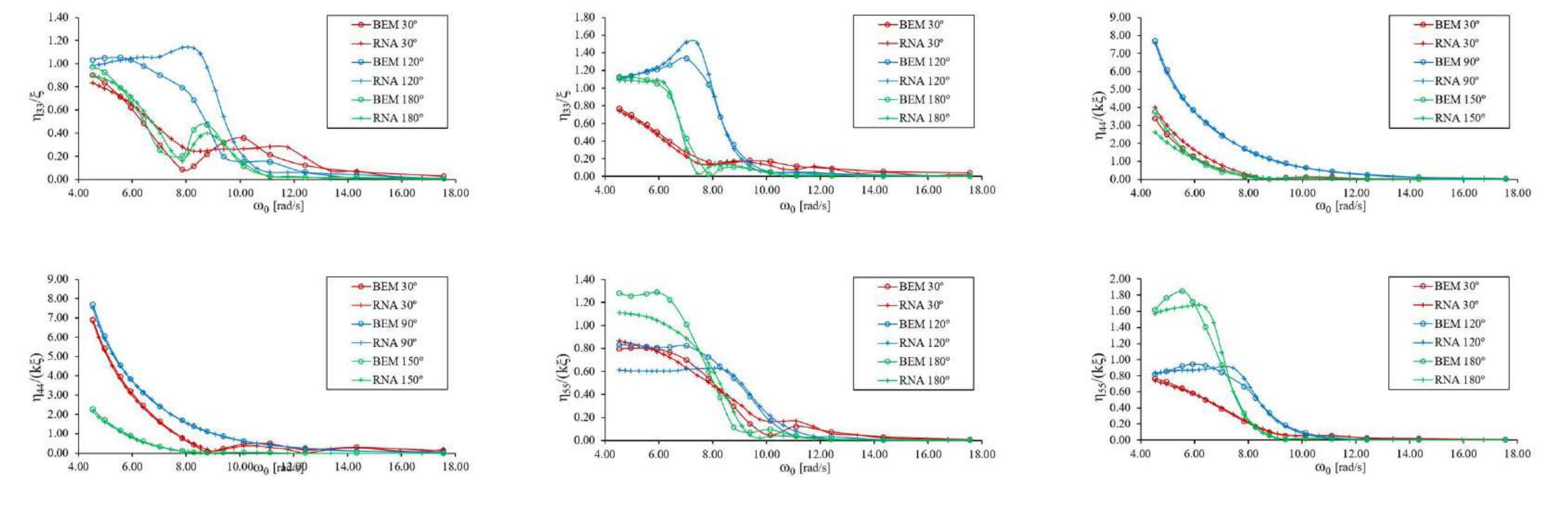
EUROPEAN UNIVERSITY OF TECHNOLOGY
"Think human first"

TRANSFORMANDO LOS OCÉANOS: INNOVACIÓN e ingeniería naval para un mundo CONECTADO y SOSTENIBLE

CIIN 2024
63° Congreso Internacional de Ingeniería Naval e Industria Marítima

CIMNE
EXCELENCIA SEVERO OCHOA

V. Results: Yacht



V. Results: Summary

Prediction error :

$$NRE_i = \frac{|t_i^* - p_i^*|}{máx(1, |t_i^*|)}$$

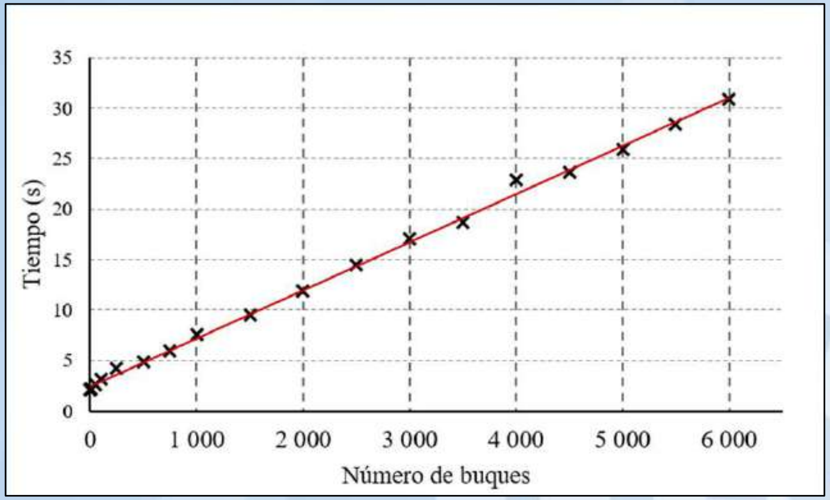
$$MNRE = \sqrt{\frac{\sum_{i=1}^{n} NRE_i^2}{n}}$$

Results:

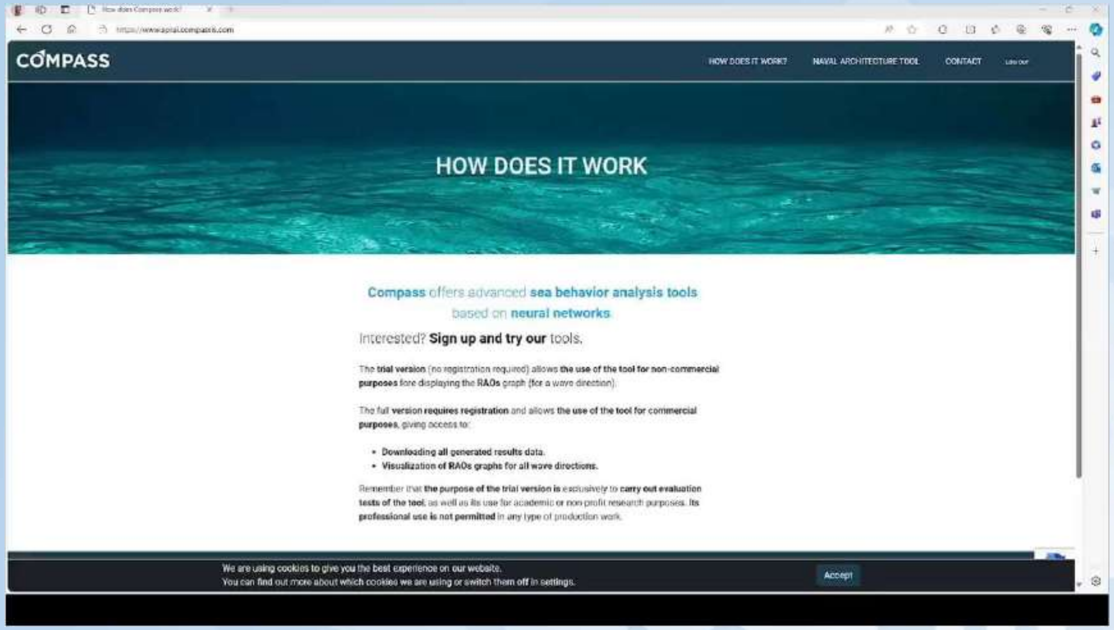
- In the added mass and damping matrices we have an average MNRE of **6,09 %** y **5,21 %**.
- The average MNRE of the sine and cosine terms of the excitation forces are **3,95 %** y **3,69 %**.
- The average MNRE for RAOs typically less than **1 %**.

VI. Conclusions

- **ANNs** to predict hydrodynamic loads for **seakeeping in the early stages of design** without the need to know the exact hull **geometry**. Fn range **0,025 to 0,30**.
- An **extensive**, **comprehensive** and **generalised database** has been generated.
- **A large number of ANNs** have been generated and trained with a large number of **hyperparameter** combinations to identify the best ANN.
- The **ANNs** developed show **similar accuracy** to the **BEM** codes.
- **Speed up to 4.000** is achieved compared to a conventional calculation code.



VI. Conclusions



Thanks for your time

SPRAI: Seakeeping prediction using artificial intelligence

pablo.romero@upct.es