Vertical motions assessment of an Offshore Supply Vessel in concept design stage

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Abstract. The main hydrodynamic characteristics of an Offshore Vessel are mostly referring to motion behaviour in rough sea. For such kind of ships, good seakeeping performances are mandatory, and, besides dynamic positioning quality, maybe more relevant than purely propulsive issues. The seakeeping performances of a ship are strongly influenced by main geometric parameters selected since concept design stage. Means that, to improve the designers' ability to properly select the best preferred design, enhanced methods should be implemented in such a way to accurately determine seakeeping performances as function of the more significant geometrical parameters and non-dimensional ratios. In the present work a procedure, based on the determination of multiple regression models with different parameter combinations, has been developed to reproduce the vertical motions transfer functions of a generic supply vessel at different encounter angles and operational speeds. The regressions have been obtained from 2D strip theory calculations on a family of supply vessels, ensuring a sufficiently accurate estimate of heave and pitch motions since concept design stage. Besides, the transfer functions have been also determined with the application of a trained neural network and the results have been compared with regressions outcomes on a reference hull.

Keywords. Concept design, Multiple regressions, Neural networks, Vertical motions

1. Introduction

The seakeeping characteristics of a vessel are strongly influenced by its main geometrical characteristics. In fact, compared to other hydrodynamic qualities like resistance, that can be easily improved in a second phase acting locally on specific hull parts, motions are strictly related to main vessel dimensions and coefficients[1][2].

By stating that, it is of primary importance the accurate selection of the main geometric characteristics since conceptual design stage[3][4], where the main decision regarding vessel dimensions are taken. In particular for offshore vessels like Platform Supply Vessels (PSV) the reduction of motions is of primary importance[5], since they should be

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able to operate in harsh sea environment for a significant part of their operational life. In fact, once the seakeeping characteristics should be improved in a second phase, they will necessary implicate difficult and expensive modifications that not always will result in the desired improvements or feasible designs[6].
To easily perform calculations in conceptual design stage it is accepted to use simple formulations while ensuring a sufficiently accurate level for attribute prediction[7]. For this purpose the transfer functions of the vertical motions have been evaluated on a family of PSV and then used to build general regression formulae, suitable to reproduce the behaviour of the vessel in regular and irregular seas.
The obtained regressions function have been then applied to a PSV not included in the initial family and compared with results coming from direct calculation and the application of a neural network on the database itself.

2. PSVs' hull form generation

To build a suitable seakeeping calculation model for initial design, it is first necessary to find a hull family to perform dedicated calculations. In order to do that, the main geometrical parameters of the existing PSV fleet should be analysed in order to identify the main dimension range of interests. Analysing the data with non-dimensional therms it has been observed that considering L/B, B/T and C_B values inside the database, distribution is quite uniform between certain ranges.
For such a reason it has been selected to build a family of supply vessel varying these three main parameters. This kind of assumption is similar to the one adopted for systematic hull series development, like FDS[8], but imply to respect some constraints on other geometrical parameters. In fact, to be sure that modifying the hull forms the effect will be mainly on the selected parameters, it has been chosen to maintain the longitudinal centre of buoyancy LCB (-0.5% L_{BP}) and the midship coefficient C_X (0.98) constant. With these considerations, the following range has been selected:

$$0.55 \leq C_B \leq 0.75 \tag{1}$$

$$2.50 \leq \frac{B}{T} \leq 3.50 \tag{2}$$

$$4.00 \leq \frac{L}{B} \leq 5.00 \tag{3}$$

Considering the central point of the design space (L/B=4.50, B/T=3.00, C_B=0.625) a parent hull form has been developed on a reference length L_{BP}=71.30 m. Modifying it according to the imposed limitations, a total of 27 hull forms have been generated, representative of the vertices, central face point and medians of a parallelepiped in a three-dimensional space having the variables described in 1 as principal axis. In Figure 1 an example is given of a subfamily of the obtained OSVs systematic series.
On the resulting hull forms, strip theory calculations have been carried out in such a way to obtain heave and pitch transfer functions for different speeds ($Fn = 0.00$ to 0.30) and headings ($\chi = 180$, 150 and 130 deg) at the same values of λ/L. The so obtained values have been used as database for multiple linear regression analysis and neural network training.

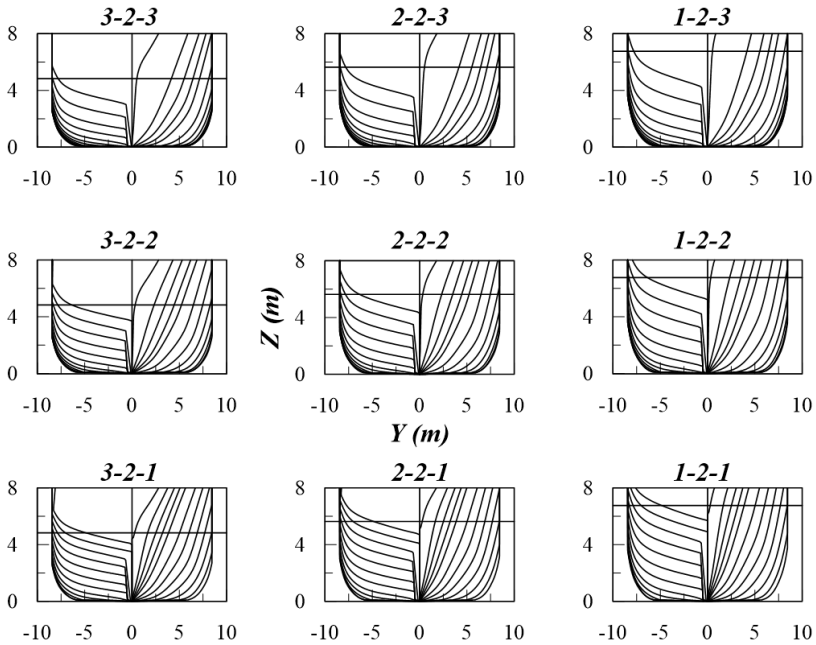

Figure 1. Midship sections of $B/T = 3.00$ PSVs subfamily

3. The regression model

Multiple linear regression (MLR) analysis is a convenient feed-forward extension of simple two variables regression analysis. Here, instead of a simple single independent variable, a set of more independent variables are used for the estimate value determination of a dependent variable. Usually the regression equation is determined using a least-square method, using the following low-order polynomials:

$$\hat{Y} = A_0 + A_1 X_1 + A_2 X_2 + \cdots + A_n X_n \tag{4}$$

that can be expressed in matrix form as:

$$Y = AX \tag{5}$$

in such a way the regression coefficient matrix A can be found from the relation:

$$A = \left(X^T X\right)^{-1} \left(X^T Y\right) \tag{6}$$

For the transfer function database, the regression analysis have been done dynamically. The basic regression equation is starting considering all the possible combinations up to the third order between L/B, B/T and C_B as independent variables, resulting in the following form:

$$trf\left(\frac{\lambda}{L}\right) = \sum_{i=0}^{3}\sum_{j=0}^{3}\sum_{k=0}^{3} A_{i+j+k}\left(\frac{L}{B}\right)^i \left(\frac{B}{T}\right)^j (C_B)^k \tag{7}$$

Table 1. General particulars of the analysed OSV.

Length between perpendiculars	L_{BP}	71.300	m
Length at design waterline	L_{WL}	75.420	m
Length overall submerged	L_{OS}	77.524	m
Breadth	B	16.000	m
Design draught	T	5.000	m
Volume	∇	3773.2	m^3
Wetted surface	S	1569.6	m^3
Bare hull wetted surface	S_0	1517.6	m^2
Appendages wetted surface	S_{APP}	52.0	m^2
Longitudinal centre of buoyancy	LCB	-1.4	$\%L_{BP}$
Block coefficient	C_B	0.630	-
Midship coefficient	C_M	0.940	-
Prismatic coefficient	C_P	0.660	-

then, the statistically irrelevant values, according to t-Student and p level values, are automatically discarded. In such a way it is possible to determine satisfactory levels of correlation coefficients R^2 and R^2_{adj}, using a restricted number of independent variables.

4. Feed-forward neural network

Artificial Neural Networks (ANN) are a mathematical model based on the similarity with successfully working biological systems, which consist of a number of units (neurons) working massively in parallel and having the capability to learn[9].
For the presented study a two layered feed-forward network with error back-propagation has been adopted, being one of the most suitable solution for such kind of approximation problems[10]. The structure to use for a feed-forward network aimed to approximate a multi-variable function $y = f(x_1, x_2, \cdots, x_n)$, presuppose the use of n neurons in the *input* layer and one in the output one. The m number of neutrons in the hidden layers can vary case by case. In the specific two hidden layers with 10 neurons each have been used both for heave and pitch transfer function determination, considering 3 neurons for input, representative of the three design space variables.
The network was trained with the Levenberg-Marquardt[11] learning algorithm, being one of the most appropriate solutions for accurately train error back-propagation neural network.
Then the samples of input matrix are randomly divided into three sets: training samples (70%), validation samples (15%) and testing samples (15%). During validation process the generalization possibility of the network are examined, while the independent verification of network performances has been made by testing the data set previously executed during training and validation process. Network performances have been evaluated by means of correlation coefficient R between 'starting' transfer function values and one obtained as network output. The obtained R values, all above 0.998, highlights the good quality of the neural network approximation capabilities.

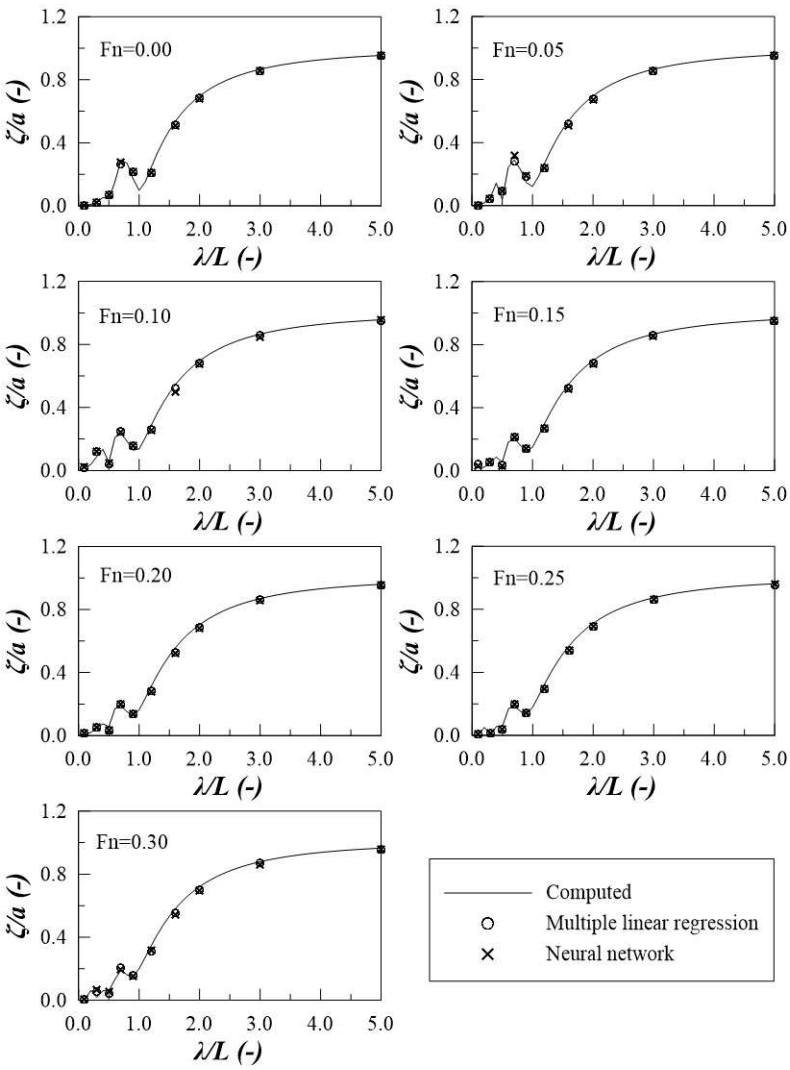

Figure 2. Transfer functions for heave motion at heading 180 deg and different vessel speeds.

5. Comparison

Based on the above mentioned techniques, heave and pitch transfer function have been evaluated for the family of OSV described in Section 2. To evaluate which of the two methods is more suitable to reproduce the vertical motions, MLR and ANN have been compared to direct 2D strip theory calculation on a OSV hull different from the parent hull but having the main parameters inside the systematic series limits. The data of the considered supply vessel are listed in table 1.

A comparison between the obtained transfer functions can be found in Figure 2 for the heave motion at 180 degrees and in Figure 3 for the pitch motion at 150 degrees. It can be appreciated that both the models are reproducing quite well the computed transfer func-

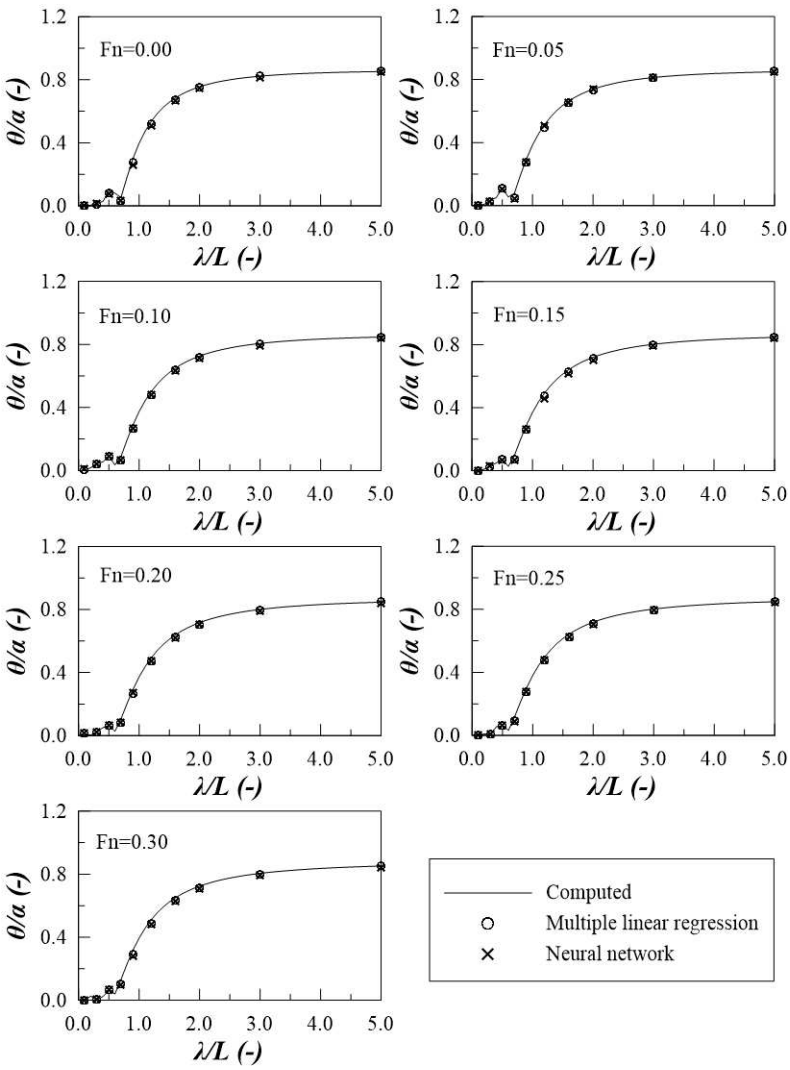

Figure 3. Transfer functions for pitch motion at heading 150 deg and different vessel speeds.

tions, resulting in R^2 values above 0.980 through the whole speed range. In both cases the accuracy level between the two methods is somewhat in favour of MLR technique.
To further investigate on the differences between ANN and MLR in seakeeping quantity predictions, a comparison has been made on the *rms* values of heave and pitch motions in irregular waves. On this purpose, dedicated calculations have been made considering the mean *rms* value for a possible operative sea area (Area 68), considering Bretschneider wave spectra.
The obtained results are reported in Table 2 for heave motion and in Table 3 for pitch motion. From the reported data it can be seen how both ANN and MLR are giving an appreciable result regarding motion predictions, giving a maximum error under 3.5% for heave motion and under 8.5% for pitch motion.

Table 2. Heave mean *rms* value for Area 68

$Fn = 0.00$						
χ	180°		150°		120°	
Computed	0.392	-	0.429	-	0.547	-
MLR	0.383	2.29%	0.421	1.86%	0.543	0.73%
ANN	0.383	2.29%	0.420	2.09%	0.542	0.91%
$Fn = 0.10$						
χ	180°		150°		120°	
Computed	0.423	-	0.459	-	0.564	-
MLR	0.414	2.12%	0.451	1.74%	0.560	0.70%
ANN	0.409	3.30%	0.450	1.96%	0.561	0.53%
$Fn = 0.20$						
χ	180°		150°		120°	
Computed	0.470	-	0.499	-	0.578	-
MLR	0.457	2.76%	0.488	2.20%	0.571	1.21%
ANN	0.455	3.19%	0.488	2.20%	0.571	1.21%

Table 3. Pitch mean *rms* value for Area 68

$Fn = 0.00$						
χ	180°		150°		120°	
Computed	1.075	-	1.065	-	0.883	-
MLR	1.044	2.88%	1.034	2.91%	0.851	3.64%
ANN	1.044	2.88%	1.008	5.35%	0.813	7.92%
$Fn = 0.10$						
χ	180°		150°		120°	
Computed	1.081	-	1.051	-	0.822	-
MLR	1.037	4.07%	1.008	4.09%	0.788	4.13%
ANN	0.995	7.95%	1.009	3.99%	0.782	4.86%
$Fn = 0.20$						
χ	180°		150°		120°	
Computed	0.973	-	0.946	-	0.748	-
MLR	0.924	5.03%	0.901	4.75%	0.717	4.14%
ANN	0.915	5.96%	0.880	6.97%	0.688	8.02%

Analysing more in detail the two methodologies results, for the considered case it can be stated that the MLR is giving a more accurate estimation of ship motions, being able to reduce the error from direct calculation up to also 2% compared to ANN for the pitch motion case. Regarding heave motion the results are more closed one to each other, but also here MLR are giving results with 1% more accuracy with respect to ANN. In any case all the obtained results are sufficiently accurate to be used in a concept design phase.

6. Conclusions

The prediction of vertical motion in an early design stage have been here investigated on a PSV. For this purpose multiple regression modelling and neural network training have

been applied on the transfer functions evaluated for a PSV's family for different speeds and headings.
The two investigated solutions are able to reproduce with a good approximation the transfer functions of the starting hull family, considering all the tested headings and speeds. The application of the neural network is giving a slightly less accurate estimate of the transfer functions with respect to regression analysis, difference that is reflected on the *rms* values determination. Beside that, regressions are giving the final results in less time compared to neural network, so they can be easily been used inside a concept design selection procedure. Further studies will be needed to highlight the behaviour of the two methods of more complex databases, where the attributes dependency cannot be restricted to the selected three variables of the systematic series.

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