Prediction of Manoeuvring Characteristics in the Concept Design of a Destroyer

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Abstract. Manoeuvring is one of the fundamental qualities of the ship. It has a direct impact on the operability of the unit and therefore on the shipowner's perception of quality. Furthermore, the manoeuvrability forecasting models are extremely sensitive to the geometry of the hull and appendages and thus closely related with the type of the unit. In this article, an innovative methodology for predicting the manoeuvring characteristics during the conceptual design phase is presented. It may be applied to all types of vessels, especially those requiring a specific study of manoeuvrability, such as fast hulls. Here, a destroyer has been considered. Starting from 15 hulls geometries, a fleet of 225 ships has been generated, by changing systematically the ratio L/B, B/T and the block coefficient C_B. This way a 3-dimensional *Central Composite Circumscribed (CCC)* has been obtained, that comprehends a total of 15 experimental points for each base hull. Manoeuvring calculations has been performed on each vessel of the fleet and the main manoeuvring dimensionless quantities has been related to some simple variables, known during the conceptual phase. With a greedy approach, the adjusted coefficient of determination $\overline{R}^2$ has been maximized. This way, from the collected data, the best possible linear models for manoeuvring characteristics are obtained. This is because no statistical significance filtering of the variables is performed, as instead happens in the classic stepwise approach.

Keywords. Manoeuvring, Coefficient of Determination, Stepwise Regression, Design of Experiment, Concept Design

1. Introduction

As highlighted by in the Annual Overview of Marine Aasualties and Incidents drawn up by EMSA [1], excluding human errors, most of the accidents between 2014 and 2021 are related issues. Indeed, manoeuvring qualities are of great importance for maritime safety and environmental protection. Moreover, operational and manoeuvring characteristics play a crucial role in determining the perception of quality of the final product [2]. Therefore, predicting and optimizing these characteristics during the initial stages of project development, particularly during the concept design phase, is of particular interest.

Several approaches have been explored for concept design of complex products such as ships. The main two are the *Holistic ship design* [5,6], based on the optimization of a single design (*Multi-Objective Decision Making (MODM)*), and the metamodel methods [7,8], which instead is based on the selection of the best design alternative (*Multi-Attributive Decision Making (MADM)*). Their common purpose is to select the best design from the Pareto front, supported by *Multi Criteria Decision Making (MCDM)* techniques, which require a model for each parameterized ship quality, such as manoeuvring characteristics.

There are various methods available to study manoeuvring qualities, such as *Manoeuvring Modeling Group (MMG)* models [3], possibly complemented with *Computational Fluid Dynamics (CFD)* predictions of derivatives [4]. While these provide valid results during the functional design phases, they can be too time-consuming and precise for the conceptual and preliminary stages. Therefore, a simpler and heuristic approach, although less accurate, is preferred.

Here, in the framework of MADM methods for the selection of the best possible design alternative, to predict the behavior of manoeuvrability characteristics, the results of manoeuvring simulations were expressed as function of some global variables. The question is how to choose them, from a bigger set of global quantities. The most commonly adopted approach in various fields is *stepwise* algorithm [20,21], which aims to maximize the adjusted determination coefficient $\overline{R}^2$, while minimizing the mean squared deviation from the regression model. The stepwise algorithm gradually eliminates independent variables to select the model with the highest determination coefficient, progressively increasing the statistical significance of the regressors.

However, due to the high sensitivity of manoeuvrability results to input variables, it is helpful to disengage from the concept of statistical significance. Furthermore, there is a large body of literature criticizing the stepwise method, mainly because of the inflaction of false positive findings [22,23,24]. For these reasons, a greedy approach has been here adopted.

The purpose is to build a predictive model for manoeuvrability, such as to maximize the adjusted coefficient of determination $\overline{R}^2$. To better illustrate the methodology, a case study is presented. Although the obtained results are strongly dependent on the unit considered, this methodology is applicable during the concept design phase to all vessels that require special care concerning manoeuvrability.

2. Materials and Methods

Using the MADM method, the first step involves defining the design space that encompasses all design alternatives. The response datas are the results of manoeuvrability simulations for each alternative. To establish a correlation between the independent input variables with response, the dataset has been normalized, and the outliers have been removed. Finally, a criterion is proposed for selecting the optimal combination of repressors, based on maximizing the adjusted coefficient of determination $\overline{R}^2$.

2.1. Design Space

First of all, it is necessary to identify a *design space*, characterized by few main characteristics of the ship. These variables should be known during the conceptual phase. A standard multipurpose design space has been here adopted, useful for other metamodels, such as seakeeping and stability ones. The design space consists of the following free variables:

- Ratio between length and breadth L/B;

Table 1. Central Composite Circumscribed (CCC)

Alternative	$\frac{L}{B}$	$\frac{B}{T}$	C_B
00	$\left(\frac{L}{B}\right)_0$	$\left(\frac{B}{T}\right)_0$	$(C_B)_0$
01	$\left(\frac{L}{B}\right)_0-\Delta\left(\frac{L}{B}\right)$	$\left(\frac{B}{T}\right)_0-\Delta\left(\frac{B}{T}\right)$	$(C_B)_0-\Delta C_B$
02	$\left(\frac{L}{B}\right)_0+\Delta\left(\frac{L}{B}\right)$	$\left(\frac{B}{T}\right)_0-\Delta\left(\frac{B}{T}\right)$	$(C_B)_0-\Delta C_B$
03	$\left(\frac{L}{B}\right)_0-\Delta\left(\frac{L}{B}\right)$	$\left(\frac{B}{T}\right)_0+\Delta\left(\frac{B}{T}\right)$	$(C_B)_0-\Delta C_B$
04	$\left(\frac{L}{B}\right)_0+\Delta\left(\frac{L}{B}\right)$	$\left(\frac{B}{T}\right)_0+\Delta\left(\frac{B}{T}\right)$	$(C_B)_0-\Delta C_B$
05	$\left(\frac{L}{B}\right)_0-\Delta\left(\frac{L}{B}\right)$	$\left(\frac{B}{T}\right)_0-\Delta\left(\frac{B}{T}\right)$	$(C_B)_0+\Delta C_B$
06	$\left(\frac{L}{B}\right)_0+\Delta\left(\frac{L}{B}\right)$	$\left(\frac{B}{T}\right)_0-\Delta\left(\frac{B}{T}\right)$	$(C_B)_0+\Delta C_B$
07	$\left(\frac{L}{B}\right)_0-\Delta\left(\frac{L}{B}\right)$	$\left(\frac{B}{T}\right)_0+\Delta\left(\frac{B}{T}\right)$	$(C_B)_0+\Delta C_B$
08	$\left(\frac{L}{B}\right)_0+\Delta\left(\frac{L}{B}\right)$	$\left(\frac{B}{T}\right)_0+\Delta\left(\frac{B}{T}\right)$	$(C_B)_0+\Delta C_B$
09	$\left(\frac{L}{B}\right)_0+\sqrt{3}\Delta\left(\frac{L}{B}\right)$	$\left(\frac{B}{T}\right)_0$	$(C_B)_0$
10	$\left(\frac{L}{B}\right)_0-\sqrt{3}\Delta\left(\frac{L}{B}\right)$	$\left(\frac{B}{T}\right)_0$	$(C_B)_0$
11	$\left(\frac{L}{B}\right)_0$	$\left(\frac{B}{T}\right)_0+\sqrt{3}\Delta\left(\frac{B}{T}\right)$	$(C_B)_0$
12	$\left(\frac{L}{B}\right)_0$	$\left(\frac{B}{T}\right)_0-\sqrt{3}\Delta\left(\frac{B}{T}\right)$	$(C_B)_0$
13	$\left(\frac{L}{B}\right)_0$	$\left(\frac{B}{T}\right)_0$	$(C_B)_0+\sqrt{3}\Delta C_B$
14	$\left(\frac{L}{B}\right)_0$	$\left(\frac{B}{T}\right)_0$	$(C_B)_0-\sqrt{3}\Delta C_B$

- Ratio between breadth and draft B/T;
- Block coefficient C_B.

Other characteristic parameters can be derived from these, such as $L/T = L/B \cdot B/T$.

Different ships, belonging to the same class, are represented in the design space by distinct points. The manoeuvring calculations has been performed on the ships related to these points.

To extend the dataset, a *Central Composite Circumscribed (CCC)* [9], characterized by three factors; the free coordinates of the design space $(L/B, B/T, C_B)$; and two levels $\Delta = \pm 1$ has been used. The total of 15 experimental points obtained, were arranged as shown in Table 1.

2.2. *Data Normalization and Outlier Removal*

As proposed by Degan et al. [10], a set of r independent variables, considered significant in the representation of the phenomenon, and s object of observation – the *dependent variables* or *response variables* – were chosen. The n collected data points can be arranged in two matrices:

- The input matrix $\mathbf{X}$ with dimension $n \times r$, where each element X_{ij} represents the value of the j-th independent variable X_j for the i-th data point;
- The output matrix $\mathbf{Y}$ with dimension $n \times s$, where each element Y_{ij} represents the value of the j-th dependent variable Y_j for the i-th data point.

To ensure consistency in the data, all columns of the matrices are normalized separately using their minimum and maximum values. Each element of the normalized column-vector $\vec{Z}'$ is obtained as follows:

$$z_i' = \frac{z_i - c}{r} \qquad \forall z_i \in Z$$

where

$$c = \frac{\max(\vec{Z}) + \min(\vec{Z})}{2} \qquad\qquad r = \frac{\max(\vec{Z}) - \min(\vec{Z})}{2}$$

Once normalized, *outliers*[1] on dependent variables $Y_1, ..., Y_s$ were removed. Each normalized column is then de-normalized and re-normalized without outliers until no more outliers were found.

2.3. *Multiple linear regression*

Multiple linear regression has been employed to establish the correlation between the input data matrix $\mathbf{X}$ and the output data matrix $\mathbf{Y}$ [12]. As a matter of fact, the least square method can be extended to the multi-dimensional case. Given a set of n records and k regressors, the independent variables $X_1, ..., X_k$, the objective is to find $k+1$ parameters $p_0, p_1, ..., p_k$ that minimize the sum of the Euclidean distances between the k-dimensional hyperplane defined by these parameters and the n observed data. The equation for the k-dimensional hyperplane is given by:

$$\hat{y}(\vec{x}) = p_0 + p_1 X_1 + p_2 X_2 + ... + p_k X_k$$

This problem can be rewritten using the overdetermined linear system:

$$\vec{y} = \mathbf{X}\vec{p} + \vec{\varepsilon}$$

where

$$\vec{y} = \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \qquad \mathbf{X} = \begin{bmatrix} 1 \; X_{11} \; \dots \; X_{1k} \\ \vdots \\ 1 \; X_{1k} \; \dots \; X_{nk} \end{bmatrix} \qquad \vec{p} = \begin{bmatrix} p_0 \\ p_1 \\ \vdots \\ p_k \end{bmatrix} \qquad \vec{\varepsilon} = \begin{bmatrix} y_0 - \hat{y}(\vec{X}_0) \\ y_1 - \hat{y}(\vec{X}_1) \\ \vdots \\ y_n - \hat{y}(\vec{X}_n) \end{bmatrix}$$

Here, $\vec{\varepsilon}$ represents the *residuals* vector, which denotes the distance between the known point y_0 and the expected value $\hat{y}(\vec{X}_0)$. Applying the least square method [13] the pa-

[1] Commonly, the *outliers* of a dataset are the values that exceed one and a half *interquartile range* Δ_{iq}, under the first quartile q_1 and over the last q_3 [11].

rameters $k+1$ parameters that minimize the sum of squared residuals can be determined as:

$$\vec{p} = \left(\mathbf{X}^T\mathbf{X}\right)^{-1}\mathbf{X}^T\vec{y}$$

Thus, by selecting a subset of k regressors from the independent variables $X_1, X_2, \ldots, X_r$ defined earlier, it is possible to predict trends of manoeuvring characteristics – during concept design – with a simple multiple linear regression model.

2.4. *Maximum $\overline{R}^2$ Criterion*

The coefficient of determination R^2 increases monotonically with the number of independent variables added to the model, even if they are completely uncorrelated with the phenomenon. This is because the precision in representing the phenomenon increases with the addition of more degrees of freedom. Therefore, the coefficient of determination is not adequate to assess the reliability of a multiple regression model.

To better understand the benefits associated with adding a new independent variable, the coefficient of determination shall be corrected by defining the *adjusted coefficient of determination* $\overline{R}^2$ as follows:

$$\overline{R}^2 = 1 - \frac{n-1}{n-k-1} \cdot \frac{RSS}{TSS} = 1 - \frac{(1-R^2)(n-1)}{n-k-1}$$

Where n is the number of datas observed and k is the number of *regressors*. In any case is $\overline{R}^2 \leq R^2$ and $\overline{R}^2$ is not dependent in k.

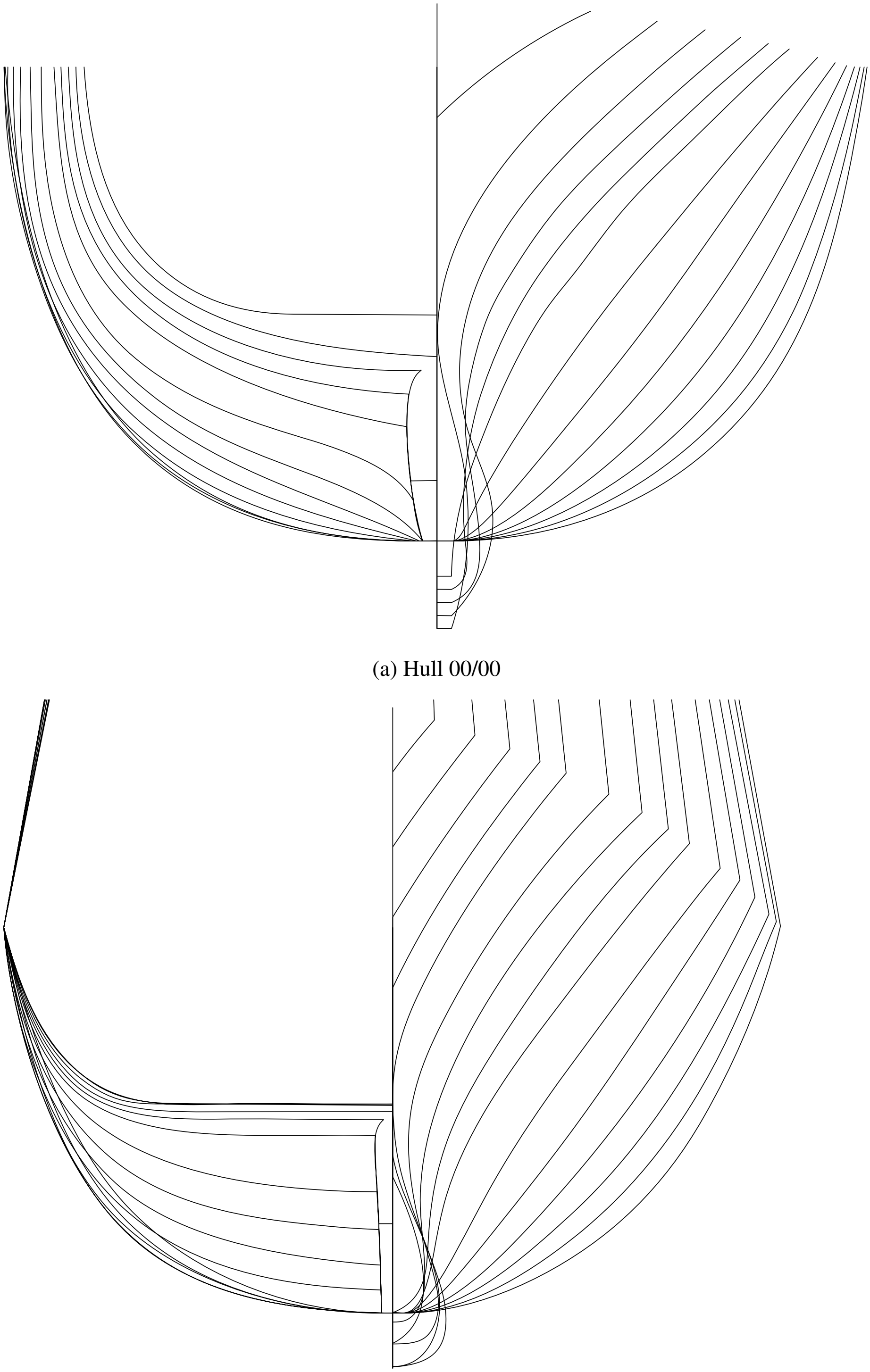
From the set of independent variables up to the second order (Tab. 5), the most representative k regressors has been chosen adopting a *greedy* approach. Each combination of available independent variables $X_1, \ldots, X_r$ is evaluated as regressors in a multiple linear regression model. The combination that maximize the *adjusted determination coefficient* $\overline{R}^2$ is adopted. Unlike the *stepwise* approach, this method is independent of statistical significance and does not involve the p-value based selection.

3. Application

3.1. *Case Study*

The process is here applied to a case study, consisting in the initial design of a destroyer. Initially, a fleet of 15 destroyers were considered. The body plan of two of them are represented in Figure 1a and Figure 1b. In the design space, the ships are equivalent alternatives, corresponding to 15 distinct and non-aligned points. For each destroyer – each *design point* – 14 more ships were generated with the Lackenby method [14], following the *central composite design* previously defined (Tab. 1). Since 15 variants were obtained for each of the 15 ships, the database consist of 255 units (Tab. 2).

The commercial manoeuvring calculator *AVEVA Initial Design*, based on classical maneuvering theory [15,16], has been adopted to perform the following standard manoeuvring tests [17]:



(a) Hull 00/00

(b) Hull 07/00

Figure 1. Body plan

Table 2. Limits of the fleet

	L/B	B/T	C_B
Min	7.126	3.099	0.406
Max	8.349	3.601	0.538

Table 3. Dependent variables

(a) Turning cirlce

Result	$v_1 = 12\,kn$		$v_2 = 18\,kn$	
	$\delta = 15^o$	$\delta = 35^o$	$\delta = 15^o$	$\delta = 35^o$
Advance/L (90^o)	$Y_{1,1}$	$Y_{6,1}$	$Y_{1,2}$	$Y_{6,2}$
Transfer/L (90^o)	$Y_{2,1}$	$Y_{7,1}$	$Y_{2,2}$	$Y_{7,2}$
Tactical D/L (180^o)	$Y_{3,1}$	$Y_{8,1}$	$Y_{3,2}$	$Y_{8,2}$
St. turning D/L (360^o)	$Y_{4,1}$	$Y_{9,1}$	$Y_{4,2}$	$Y_{9,2}$
V_S/V_{appr}	$Y_{5,1}$	$Y_{10,1}$	$Y_{5,2}$	$Y_{10,2}$

(b) Zig-zag manoeuvre

Result	$v_1 = 12\,kn$		$v_2 = 18\,kn$	
	$\delta = \pm 10^o$	$\delta = \pm 20^o$	$\delta = \pm 10^o$	$\delta = \pm 20^o$
1st OvSh	$Y_{11,1}$	$Y_{13,1}$	$Y_{11,2}$	$Y_{13,2}$
2nd OvSh	$Y_{12,1}$	$Y_{14,1}$	$Y_{12,2}$	$Y_{14,2}$

- Turning circle at rudder angle $\delta = 15^o$;
- Turning circle at rudder angle $\delta = 35^o$;
- Zig-zag manoeuvre $10^o/10^o$;
- Zig-zag manoeuvre $20^o/20^o$.

Each one repeated at speed of 12 kn and 18 kn. This way, 28 dependent variables have been defined, named as for Table 3. In Table 4 are reported the manoeuvring results obtained for six ships of the fleet.

The independent variables were defined combining the design space free coordinates L/B, B/T, C_B, the Froude number F_n and the inertia radius. Among these, with the previously described greedy approach, the best k regressors have been chosen. For the estimation of the roll inertia radius k_{xx}, the empirical formulation of Doyere [18] has been adopted, whereas for the pitch inertia radius k_{yy} the Pavlenko one [19].

$$k_{xx} = \sqrt{\frac{1}{12}\left(B^2 + 4\overline{KG}^2\right)} \qquad k_{yy} = \sqrt{0.65 \cdot C_{WP} L^2}$$

The 16 adimensional variables thus generated are reported in Table 5.

3.2. Results and Discussion

Applying the greedy approach for the maximization of the adjusted coefficient of determination $\overline{R}^2$, each dependent variable $Y_{1,1},\ldots,Y_{14,1},Y_{1,2},\ldots,Y_{14,2}$ has been defined as a

Table 4. Manoeuvring results for some hulls

Hull	00/00	00/05	00/10	07/00	07/05	07/10
L_{WL}	162.44	164.62	162.41	158.20	160.15	158.22
B_{WL}	20.62	20.90	20.62	22.20	20.19	19.95
T	6.30	6.43	6.30	6.25	6.35	6.25
L/B	7.76	7.75	7.75	7.13	7.93	7.93
B/T	3.27	3.25	3.27	3.55	3.18	3.19
C_B	0.48	0.50	0.48	0.42	0.45	0.46
$Y_{1,1}$	3.47	3.41	3.47	3.91	3.76	3.78
$Y_{2,1}$	2.37	2.31	2.37	2.84	2.73	2.75
$Y_{3,1}$	5.15	5.03	5.15	6.15	5.89	5.93
$Y_{4,1}$	4.97	4.83	4.97	6.04	5.79	5.81
$Y_{5,1}$	0.83	0.82	0.83	0.87	0.87	0.87
$Y_{6,1}$	2.13	2.10	2.13	2.35	2.25	2.26
$Y_{7,1}$	1.10	1.07	1.10	1.32	1.26	1.28
$Y_{8,1}$	2.38	2.31	2.38	2.87	2.72	2.73
$Y_{9,1}$	1.85	1.76	1.85	2.49	2.37	2.36
$Y_{10,1}$	0.54	0.52	0.54	0.60	0.61	0.61
$Y_{11,1}$	5.06	5.61	5.07	4.71	4.11	3.84
$Y_{12,1}$	6.24	6.54	6.25	4.62	3.61	4.97
$Y_{13,1}$	11.48	10.97	11.48	10.03	10.09	9.45
$Y_{14,1}$	11.93	12.33	11.93	11.41	10.43	9.25
$Y_{1,2}$	3.45	3.38	3.34	3.93	3.76	3.79
$Y_{2,2}$	2.35	2.28	2.35	2.85	2.73	2.75
$Y_{3,2}$	5.12	4.98	5.12	6.17	5.89	5.93
$Y_{4,2}$	4.95	4.81	4.95	6.06	5.79	5.83
$Y_{5,2}$	0.85	0.84	0.85	0.88	0.87	0.87
$Y_{6,2}$	2.21	2.16	2.21	2.46	2.35	2.36
$Y_{7,2}$	1.10	1.07	1.11	1.35	1.28	1.29
$Y_{8,2}$	2.38	2.30	2.38	2.91	2.74	2.75
$Y_{9,2}$	1.87	1.77	1.87	2.52	2.39	2.38
$Y_{10,2}$	0.55	0.54	0.55	0.60	0.62	0.61
$Y_{11,2}$	5.70	5.83	5.71	3.56	4.12	4.22
$Y_{12,2}$	7.04	7.52	7.04	4.82	3.61	5.74
$Y_{13,2}$	14.86	14.63	14.87	12.15	11.35	10.67
$Y_{14,2}$	15.32	15.01	15.32	11.26	11.36	13.17

function of with the best combination of independent variables $X_1,...,X_{16}$. In Table 6 and Table 7 are reported these optimal combinations together with the resulting $\overline{R}^2$ and the regression coefficients p_i.

The minimum, average, and maximum $\overline{R}^2$ values obtained are 0.414, 0.792, and 0.917, respectively. The lower $\overline{R}^2$ values affect the results of the zig-zag manoeuvre test ($Y_{11,1}, Y_{12,1}, Y_{13,1}, Y_{14,1}, Y_{11,2}, Y_{12,2}, Y_{13,2}, Y_{14,2}$). This means that none of the regressors here considered has a high-level of determination for these responses. To improve the determination, new independent variables should be analyzed. On the other hand, the

Table 5. Independent variables

Variable	Expression	Min	Max
X_1	$\frac{T}{B}$	0.278	0.323
X_2	$\left(\frac{T}{B}\right)^2$	0.077	0.104
X_3	$\left(\frac{B}{L}\right)^2$	0.014	0.020
X_4	$C_B \cdot \left(\frac{T}{B}\right)$	0.117	0.168
X_5	$C_B \cdot \left(\frac{T}{L}\right)^2$	5.74×10^{-4}	8.74×10^{-4}
X_6	$(1-C_B) \cdot \left(\frac{T}{B}\right)$	0.140	0.180
X_7	$(1-C_B) \cdot \left(\frac{T}{L}\right)$	0.018	0.024
X_8	F_n	0.154	0.253
X_9	$F_n \cdot C_B$	0.066	0.131
X_{10}	$F_n \cdot \frac{T}{B}$	0.044	0.080
X_{11}	$F_n \cdot \frac{B}{L}$	0.019	0.035
X_{12}	$F_n \cdot \frac{T}{L}$	5.42×10^{-3}	10.7×10^{-3}
X_{13}	$\frac{F_n}{C_B}$	0.302	0.599
X_{14}	$F_n \cdot \frac{B}{T}$	0.482	0.876
X_{15}	$\frac{k_{xx}}{L} = \frac{\sqrt{\frac{1}{12}\left(B^2+4\overline{KG}^2\right)}}{L}$	0.360	0.380
X_{16}	$\frac{k_{yy}}{L} = \sqrt{0.65 C_{WP}}$	0.183	0.237

average $\overline{R}^2$ value for the turning circle responses is 0.889, considered satisfactory for concept design applications.

It should be noted that the model obtained is closely tied to the dataset. By employing a greedy approach on all possible combinations of predictors, the coefficient of determination is maximized for the chosen independent variables within the considered dataset. Expanding the training database or modifying the independent variables can further enhance the model. It is worth noting that since all possible combinations of independent variables are evaluated, the time complexity of the greedy approach is exponential in relation to the number of independent variables. The time-complexity of the stepwise algorithm remains to be explored.

4. Conclusions

By evaluating the maneuverability characteristics of various design alternatives, a specific predictive linear model has been developed for this project. The main advantage of the greedy approach employed in this study is its independence from statistical significance, as it selects the optimal combination of regressors based solely on the adjusted coefficient of determination, denoted as $\overline{R}^2$. On the other hand, the time complexity of the greedy approach is exponential with the number of independent variables, since all possible combinations of independent variables are evaluated. With the independent variables here considered, satisfactory linear regression models have been obtained for the responses of the turning circle maneuver. However, for the responses related to zig-zag maneuvers, the models models provide only indicative results.

Future studies in this area could involve the application of multiple non-linear regressions or deep learning techniques to develop models for predicting manoeuvring

L **Table 6.** Results $v_1 = 12kn$

Depndent variable	Optimal regressors	Coefficients $(p_0, ..., p_{k+1})$	$\overline{R}^2$
$Y_{1,1}$	$X_1, X_2, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{12}, X_{13}, X_{14}, X_{15}, X_{16}$	−1.81, 100.13, −97.73, −5.06, 4.22, 2.57, 3.48, −61.34, 8.54, 61.16, −7.81, 3.17, 62.97, 0.94, 0.11	0.895
$Y_{2,1}$	$X_1, X_2, X_3, X_4, X_5, X_8, X_9, X_{10}, X_{11}, X_{13}, X_{14}, X_{15}, X_{16}$	−0.54, 46.46, −45.67, 6.18, −3.47, 2.16, −26.49, 1.79, 30.07, −10.03, 1.85, 30.51, 0.54, 0.05	0.902
$Y_{3,1}$	$X_1, X_2, X_3, X_4, X_5, X_6, X_8, X_9, X_{10}, X_{12}, X_{13}, X_{14}, X_{15}, X_{16}$	−0.80, 60.16, −62.27, 1.18, −2.92, 3.52, 3.32, −41.36, 4.45, 44.03, −5.97, 2.56, 40.49, 0.71, 0.11	0.890
$Y_{4,1}$	$X_1, X_2, X_3, X_4, X_5, X_8, X_9, X_{10}, X_{11}, X_{13}, X_{14}, X_{15}, X_{16}$	−0.72, 49.74, −48.80, 5.86, −3.41, 2.13, −28.34, 1.62, 31.75, −9.54, 1.71, 32.42, 0.59, 0.07	0.895
$Y_{5,1}$	$X_1, X_2, X_3, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}$	3.42, −99.60, 97.72, 7.41, −5.73, 1.92, 65.35, −7.45, −59.41, −15.44, 4.89, −2.23, −60.09	0.865
$Y_{6,1}$	$X_1, X_2, X_3, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}, X_{15}, X_{16}$	−1.53, 119.92, −126.03, −12.75, 6.96, 7.41, 8.83, −87.66, 12.68, 88.16, 25.15, −26.27, 3.32, 78.56, 1.56, 0.21	0.887
$Y_{7,1}$	$X_1, X_2, X_3, X_4, X_5, X_6, X_8, X_9, X_{10}, X_{12}, X_{13}, X_{14}, X_{15}, X_{16}$	−1.09, 62.52, −63.10, 1.15, −2.98, 2.65, 3.13, −41.38, 4.69, 42.61, −4.69, 2.34, 41.04, 0.86, 0.10	0.912
$Y_{8,1}$	$X_1, X_2, X_4, X_5, X_6, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}, X_{15}, X_{16}$	−2.63, 110.65, −109.25, −4.18, 3.58, 4.32, −69.74, 6.75, 69.76, 2.23, −6.45, 2.93, 70.14, 1.07, 0.16	0.891
$Y_{9,1}$	$X_3, X_4, X_5, X_{10}, X_{11}, X_{13}, X_{14}, X_{15}, X_{16}$	0.40, 3.05, −1.80, 1.32, 1.53, −5.15, 0.83, 1.78, 0.48, 0.09	0.911
$Y_{10,1}$	$X_1, X_2, X_3, X_5, X_6, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{13}, X_{14}$	4.10, −142.16, 143.71, 11.01, −2.42, −9.21, 97.08, −11.32, −93.20, −23.50, 13.73, −2.60, −88.69	0.827
$Y_{11,1}$	$X_1, X_2, X_4, X_6, X_7, X_8, X_9, X_{13}, X_{14}, X_{16}$	−1.82, 55.30, −38.20, −8.29, 5.42, 0.92, −16.26, 15.32, 2.15, 21.82, −0.32	0.414
$Y_{12,1}$	$X_1, X_2, X_4, X_7, X_8, X_{10}, X_{14}, X_{15}, X_{16}$	−4.34, 139.79, −138.49, 0.81, −0.32, −81.69, 86.15, 85.26, −0.74, −0.19	0.526
$Y_{13,1}$	$X_2, X_7, X_{11}, X_{13}, X_{14}, X_{15}$	−0.36, 3.15, 1.28, −1.32, −1.90, 3.99, −1.07	0.497
$Y_{14,1}$	$X_1, X_2, X_6, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{14}, X_{16}$	1.86, −77.56, 81.00, −3.61, 53.70, −2.59, −57.51, −2.48, 3.49, −51.81, −0.11	0.552

characteristics during the concept design phase. Moreover, considering the existence of established theories for maneuverability modeling, such as the MMG (Manoeuvring Modeling Group) models [3], the development of a physics-informed machine learning framework could find excellent applications in this context. These approaches may provide more accurate and comprehensive models for specific ship designs, without signifi-

Table 7. Results $v_2 = 18kn$

Depndent variable	Optimal regressors	Coefficients $(p_0, ..., p_{k+1})$	$\overline{R}^2$
$Y_{1,2}$	$X_1, X_2, X_4, X_5, X_6, X_7, X_8, X_{13}, X_9, X_{10}, X_{12}, X_{15}, X_{14}, X_{16}$	$-1.49, 87.91, -86.34, -4.21, 3.93, 2.17, 3.56, -54.77, 2.37, 6.94, 55.54, -7.63, 0.84, 56.46, 0.13$	0.900
$Y_{2,2}$	$X_1, X_2, X_3, X_4, X_5, X_8, X_{13}, X_9, X_{10}, X_{11}, X_{15}, X_{14}, X_{16}$	$-0.37, 39.06, -38.55, 5.93, -3.13, 1.96, -22.54, 1.44, 1.28, 26.18, -9.53, 0.50, 26.37, 0.07$	0.906
$Y_{3,2}$	$X_1, X_2, X_3, X_4, X_5, X_8, X_{13}, X_9, X_{10}, X_{11}, X_{15}, X_{14}, X_{16}$	$-1.13, 60.71, -59.10, 5.75, -3.75, 2.20, -34.84, 1.64, 1.78, 38.05, -9.42, 0.64, 39.37, 0.09$	0.898
$Y_{4,2}$	$X_1, X_2, X_3, X_4, X_5, X_8, X_{13}, X_9, X_{10}, X_{11}, X_{15}, X_{14}, X_{16}$	$-0.75, 48.65, -47.42, 5.67, -3.49, 2.12, -27.61, 1.55, 1.55, 30.81, -9.31, 0.54, 31.81, 0.08$	0.900
$Y_{5,2}$	$X_1, X_2, X_4, X_5, X_6, X_7, X_8, X_{13}, X_9, X_{10}, X_{12}, X_{14}, X_{16}$	$4.84, -105.16, 97.30, 4.24, 3.47, -2.23, 6.63, 62.09, -0.99, -4.25, -54.61, -11.06, -63.12, -0.04$	0.866
$Y_{6,2}$	$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_{13}, X_9, X_{10}, X_{11}, X_{12}, X_{15}, X_{14}, X_{16}$	$-2.38, 124.68, -125.71, -6.60, -2.82, 5.63, 5.87, 5.12, -83.03, 2.99, 10.59, 82.64, 13.84, -17.11, 1.43, 79.58, 0.19$	0.897
$Y_{7,2}$	$X_1, X_2, X_3, X_4, X_5, X_6, X_8, X_{13}, X_9, X_{10}, X_{11}, X_{15}, X_{14}, X_{16}$	$-0.73, 51.17, -48.42, 5.66, -4.21, 1.62, 1.10, -28.46, 1.88, 3.89, 29.60, -8.71, 0.61, 32.53, 0.06$	0.917
$Y_{8,2}$	$X_1, X_2, X_3, X_4, X_5, X_6, X_8, X_{13}, X_9, X_{10}, X_{12}, X_{15}, X_{14}, X_{16}$	$-2.27, 100.67, -98.72, 1.30, -4.35, 3.34, 4.02, -62.47, 2.65, 6.51, 62.68, -5.58, 0.93, 63.88, 0.14$	0.893
$Y_{9,2}$	$X_3, X_4, X_5, X_{13}, X_9, X_{10}, X_{11}, X_{15}, X_{14}, X_{16}$	$0.63, 3.68, -2.58, 1.62, 1.49, 1.12, 1.36, -6.21, 0.59, 1.59, 0.09$	0.885
$Y_{10,2}$	$X_1, X_2, X_3, X_5, X_6, X_8, X_{13}, X_9, X_{10}, X_{11}, X_{12}, X_{14}$	$5.70, -181.30, 180.77, 9.15, -1.54, -7.48, 118.39, -1.34, -8.82, -116.20, -19.55, 10.75, -113.74$	0.834
$Y_{11,2}$	$X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{15}, X_{14}$	$6.13, -162.63, 154.89, -20.42, 5.49, 6.07, 6.22, 9.16, 89.66, 6.56, -96.00, 33.44, -25.60, -1.45, -103.21$	0.622
$Y_{12,2}$	$X_1, X_2, X_5, X_7, X_9, X_{11}, X_{12}, X_{14}, X_{16}$	$0.97, 9.39, -7.27, 1.67, 6.41, 5.44, 0.46, -8.38, 2.62, -0.11$	0.702
$Y_{13,2}$	$X_1, X_2, X_3, X_4, X_6, X_8, X_9, X_{10}, X_{11}, X_{12}, X_{14}, X_{16}$	$1.78, -92.33, 89.97, -18.36, 5.74, 8.72, 48.32, 5.13, -61.42, 35.63, -14.04, -63.03, -0.20$	0.657
$Y_{14,2}$	$X_3, X_5, X_7, X_8, X_{11}, X_{12}, X_{15}, X_{14}$	$-2.17, -8.78, -5.47, -5.44, -9.66, 14.69, 9.44, 1.55, -0.41$	0.443

cantly increasing the time required.

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