

DATA DRIVEN IDENTIFICATION OF SHIP MANEUVERING COEFFICIENTS

Vallabh Deogaonkar^{1,†,*}, Aditya Jadhav^{1,†}, Krishnavelu R¹, Abhilash Somayajula¹

¹Marine Autonomous Vessels (MAV) Laboratory, Indian Institute of Technology Madras, Chennai, Tamil Nadu, India

ABSTRACT

Maneuvering models of a ship are quite complex and require accurate knowledge of the various hydrodynamic derivatives and coefficients to model the maneuvering trajectories undertaken by a ship accurately. Discerning these coefficients through practical tests in specialized facilities is expensive and time-consuming. Data-driven identification of the ship maneuvering coefficients using free-running model data is a possible alternative. In this study, the maneuvering motions of the KCS hull are simulated using the MMG model, which are then used as a starting point to identify an Abkowitz model for the vessel. The coefficients of the Abkowitz model are predicted without presuming any knowledge of the MMG model used to generate the data. Three different approaches – Least squares, LASSO optimization, and Support Vector Machines – are used to identify the hydrodynamic coefficients of the Abkowitz model. The identified coefficients are used to generate test trajectories not seen in training data and are compared with the MMG model to verify that the dynamics are accurately captured. The common issue of parameter drift occurring due to the problem being ill-posed is discussed, and sparsity-based solutions are suggested to overcome them.

Keywords: System Identification, MMG, Abkowitz, SVR, LASSO, Regression

1. INTRODUCTION

The International Maritime Organization (IMO) specifies a set of standards to be followed in the initial stages of a ship design [1]. Explicit importance regarding ship maneuverability is mentioned in the rules, and hence its study becomes essential in the design process. Several approaches are available for studying ship maneuverability, including using empirical formulas, performing physical model tests, and using computer simulations. Of these approaches, computer simulations are a popular choice due to their ease of use and practicality. To perform computer-based simulations, accurate mathematical modeling is required.

These mathematical models need to be capable of simulating the dynamics of the vessel, even in the case of sharp maneuvers, where the vessel exhibits nonlinear and complex dynamics. Hence, identifying the underlying mathematical model behind the physical process becomes essential.

Some popular mathematical models include the Abkowitz [2], and the MMG model [3], which capture the underlying dynamics of the physical system using hydrodynamic coefficients. In general, these coefficients are determined through physical model tests and require multiple facilities such as towing tank with a planar motion mechanism, rotating arm facility and a sea-keeping and maneuvering basin. Unfortunately, these facilities might not all be available in one place or affordable for most researchers and designers. This poses a significant challenge in developing maneuvering models for newer vessels. However, it is far easier to get access to free-running model data that requires a single facility, such as a large basin. Since the dynamics observed in free-running experiments encode all the dynamics, a method to determine the coefficients from free-running experiments makes it easy to design accurate maneuvering models.

With the advancements in numerical optimization and machine learning, identifying the hydrodynamic characteristics from free-running model data has been gaining attention in recent years. Methods such as extended Kalman filter [4, 5], maximum likelihood method [6] and least squares, partial least squares methods [7] have been used to identify the hydrodynamic coefficients. But these methods are susceptible to simultaneous drift of parameters, ill-conditioned solutions, and sensitivity to initial conditions. ϵ -Support Vector Regression [8–10] and ν -Support Vector Regression [11] have also been used for predicting the hydrodynamic coefficients while alleviating some of these issues.

One of the key challenges in the identification of the maneuvering model from free-running trials is the unmodelled dynamics. The aim of this study is to explore the feasibility of the identification of hydrodynamic derivatives in a more general setting. In this study, the hydrodynamic derivatives of the Abkowitz model are predicted using the simulated data from the MMG model, which differs from previous studies that used sim-

[†]Joint first authors

*Corresponding author: na18b014@smail.iitm.ac.in

ulated data from the same model whose coefficients were being estimated. Regression techniques such as Least squares, LASSO optimization, and Support Vector Machines have been used to extract the hydrodynamic coefficients of Panamax Class Kiso Container Ship (KCS) from the data collected from simulations using the MMG model.

The rest of the paper is organized as follows. Section 2 explains both MMG and Abkowitz mathematical models for the KCS vessel. Section 3 explains the data generation methodology, formulation of the regression problem, and techniques used to solve it. Section 4 discusses the results obtained and compares the generalizability of the different regression techniques. Finally, section 5 concludes with a summary and discussions about future works.

2. DYNAMICS OF KCS VESSEL

The dynamics of a ship moving through water is governed by Newton's laws of motion expressed by a set of differential equations with linear and nonlinear terms, which are collectively referred to as the maneuvering equations of motion. The hydrodynamic forces on the hull are expressed in terms of the Taylor series of the change in surge, sway and yaw velocities as compared to the nominal operating point. The nominal operating point is the case where the vessel moves steadily forward at the design speed. The coefficients in this Taylor series are known as hydrodynamic coefficients and govern the dynamics of the vessel. Different maneuvering models use different parameters and coefficients to model the dynamics of the vessel. Two such models considered in this study are the MMG model (Maneuvering Modelling Group) and the Abkowitz model and Section 2.1 and 2.2 describe in detail the different parameters used in these models.

Two frames of reference are considered in both numerical models. A global coordinate system (GCS) frame O_0-x, y, z with a z -axis vertically downwards and a body-fixed coordinate system (BCS) frame $O-x_b, y_b, z_b$ with its origin at the intersection of midship, centerline and waterplane as seen in Figure 1. The x -axis of the body fixed frame is pointed along the bow, and the y -axis is towards the starboard. The surge (u), sway (v), and yaw (r) velocities in the maneuvering equations are measured in the body-fixed frames while the heading of the vessel (ψ) is given by the angle between the x -axes of the BCS and GCS.

The vessel considered in this study is the Panamax class single-screwed Kiso Container Ship (KCS) and the principal particulars of the full-scale vessel are listed in Table 1.

TABLE 1: KCS PRINCIPAL PARTICULARS

Main Particulars	Value
Length between perpendiculars $L(m)$	230
Breadth $B(m)$	32.2
Draft $d(m)$	10.8
Displacement $\nabla(m^3)$	52030
Block coefficient C_b	0.651
Radius of Gyration $R_{zz}/L(m)$	0.25

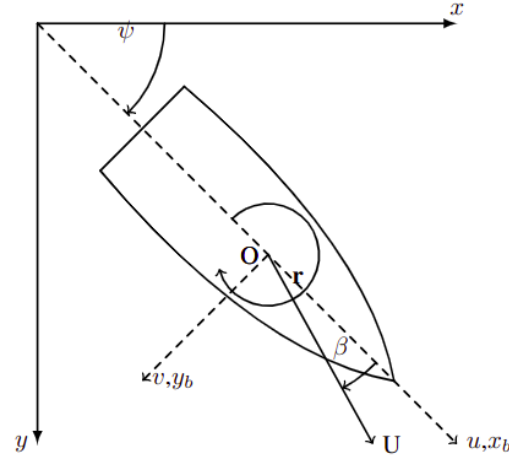


FIGURE 1: REPRESENTATION OF SHIP KINEMATIC VARIABLES

2.1 MMG Model

The Maneuvering Modeling Group (MMG) model was proposed in the Japanese Towing Tank Conference (JTTC). The model follows the Prime II non-dimensionalization system [12]. In this system, forces and moments are non-dimensionalized by $(1/2)\rho L d U^2$ and $(1/2)\rho L^2 d U^2$ respectively where L is the principal length, U is the design speed and d is the draft of the vessel. The mass and mass moment of inertia terms are non-dimensionalized by $(1/2)\rho L^2 d$ and $(1/2)\rho L^4 d$ respectively. Velocities are non-dimensionalized by U and lengths are non-dimensionalized by L .

In matrix form the MMG mathematical model [13] is given by the following equations of motion.

$$\begin{bmatrix} m' + m'_x & 0 & 0 \\ 0 & m' + m'_y & m'x'_G \\ 0 & m'x'_G & I'_{zz} + J'_{zz} \end{bmatrix} \begin{bmatrix} \dot{u}' \\ \dot{v}' \\ \dot{r}' \end{bmatrix} = \begin{bmatrix} X' \\ Y' \\ N' \end{bmatrix} \quad (1)$$

Here $[\dot{u}', \dot{v}', \dot{r}']$ denote the non-dimensional accelerations in the surge, sway and yaw directions respectively. m' and I'_{zz} are the non-dimensional mass and mass moment of inertia respectively. m'_x, m'_y are the non-dimensional surge and sway added masses respectively. J'_{zz} is the non-dimensional added mass moment of inertia in the yaw mode. The numerical values used for these parametrs are given in Table 2

TABLE 2: KCS ADDED MASS COEFFICIENTS

Non dimensional parameter	Value
Surge added mass (m'_x)	0.006269
Sway added mass (m'_y)	0.155164
Yaw added mass moment (J'_{zz})	0.009268
Yaw mass moment of inertia (I'_{zz})	0.011432
Mass of the vessel (m')	0.182280

The non dimensional external forces and moments acting on the vessel in surge, sway and yaw modes respectively are given by X', Y' and N' . These forces are decomposed into various components as described below :

$$\begin{aligned}
X' &= X'_H + X'_R + X'_C + X'_P \\
Y' &= Y'_H + Y'_R + Y'_C \\
N' &= N'_H + N'_R + N'_C
\end{aligned} \tag{2}$$

The subscripts in the above equations are denoting the components as follows:

1. H : Hydrodynamic forces and moments on the hull
2. R : Rudder forces and moments
3. C : Coriolis forces and moments arising due to non inertial midship reference frame
4. P : Propeller forces.

Since the thrust provided by the propeller is only along the surge direction, the sway and yaw components of propeller forces are taken to be zero. The details of the above hydrodynamic forces in (2) are given further.

2.1.1 Hull forces and moments. The non dimensional forces and moments acting on the hull are expressed as a Taylor series in u' , β and r' . Here u' and r' denote the non dimensional surge velocity and yaw rate respectively. β denotes the drift angle, defined as the angle between the total velocity vector of ship and its longitudinal direction and is given by $\beta = \tan^{-1}(-v'/u')$ where v' is the non dimensional sway velocity. The non dimensional hull forces and moments are given by (3) :

$$\begin{aligned}
X'_H &= X'_0 u'^2 + X'_{\beta\beta} \beta^2 + (X'_{\beta r} - m'_y) \beta r' \\
&\quad + X'_{rr} r'^2 + X'_{\beta\beta\beta} \beta^3
\end{aligned} \tag{3a}$$

$$\begin{aligned}
Y'_H &= Y'_\beta \beta + (Y'_r - m'_x) r' + Y'_{\beta\beta} \beta^2 \\
&\quad + Y'_{\beta\beta r} \beta^2 r' + Y'_{\beta rr} \beta r'^2 + Y'_{rrr} r'^3
\end{aligned} \tag{3b}$$

$$\begin{aligned}
N'_H &= N'_\beta \beta + N'_r r' + N'_{\beta\beta} \beta^2 \\
&\quad + N'_{\beta\beta r} \beta^2 r' + N'_{\beta rr} \beta r'^2 + N'_{rrr} r'^3
\end{aligned} \tag{3c}$$

The hydrodynamic coefficients for the KCS hull form are given in Table 3

2.1.2 Propeller force. The non dimensional propeller thrust force along the surge direction is given by

$$X'_P = (1 - t_p) \rho K_T D_P^4 n_P^2 / (0.5 \rho L d U^2) \tag{4}$$

where D_P is the propeller diameter, n_P is the propeller revolution rate, K_T is the propeller thrust coefficient and t_p is the thrust deduction factor. The additional resistance introduced by the propeller rotating behind the hull as opposed to the bare hull without propeller behind it is accounted by introducing the thrust deduction factor t_p . The thrust coefficient K_T is obtained by fitting a quadratic curve to the propeller open water test data and for the KCS vessel it is given by (5)

$$K_T = a_0 + a_1 J + a_2 J^2 \tag{5}$$

TABLE 3: NON-DIMENSIONAL HULL HYDRODYNAMIC DERIVATIVES FOR MMG MODEL OF KCS VESSEL

Hydrodynamic coefficient	Value
X'_0	-0.0167
$X'_{\beta\beta}$	-0.0549
$X'_{\beta r} - m'_y$	-0.1084
X'_{rr}	-0.0120
$X'_{\beta\beta\beta}$	-0.0417
Y'_β	0.2252
$Y'_r - m'_x$	0.0398
$Y'_{\beta\beta}$	1.7179
$Y'_{\beta\beta r}$	-0.4832
$Y'_{\beta rr}$	0.8341
Y'_{rrr}	-0.0050
N'_β	0.1111
N'_r	-0.0465
$N'_{\beta\beta}$	0.1752
$N'_{\beta\beta r}$	-0.6168
$N'_{\beta rr}$	0.0512
N'_{rrr}	-0.0387

Here J represents the advance coefficient and is given by (6)

$$J = \frac{u(1-w)}{n D_P} \tag{6}$$

where w represents the effective wake fraction. The effective wake fraction w accounts for the reduction in inflow fluid velocity to the propeller when operating in the wake of the hull. The values of the above mentioned propeller parameters for the KCS hull form are given in Table 4

TABLE 4: PROPELLER PARAMETERS

Parameter	Non-dimensional value
t_P	0.207
D_P	0.03435
n_P	35.86
w	0.355
a_0	0.5228
a_1	-0.4390
a_2	-0.0609

2.1.3 Rudder forces and moments. The non dimensional forces and moments due to rudder are expressed as follows :

$$X'_R = -(1 - t_R) F_N \sin \delta \tag{7a}$$

$$Y'_R = -(1 + a_H) F_N \cos \delta \tag{7b}$$

$$N'_R = -(x_R + a_H x_H) F_N \cos \delta \tag{7c}$$

where δ is the instantaneous rudder angle, t_R is the steering resistance deduction factor, x_R is the non dimensional position of rudder along the longitudinal direction of ship measured from

midship and x_H is the non dimensional position of the point where additional lateral force induced by steering is acting. F_N is the non dimensional rudder normal force and is calculated as in (8)

$$F_N = \frac{A_R}{Ld} f_\alpha U_R^2 \sin \alpha_R$$

$$\alpha_R = \delta - \tan^{-1} \left(\frac{-v_R}{u_R} \right) \quad (8)$$

where A_R is the movable rudder area, U_R is the non dimensional rudder inflow velocity, α_R is the non dimensional rudder inflow angle and f_α is the gradient of the rudder lift coefficient and it is approximated as a function of rudder aspect ratio (λ), as follows

$$f_\alpha = \frac{6.13\lambda}{2.25 + \lambda} \quad (9)$$

u_R and v_R are the longitudinal and lateral inflow velocity components to rudder respectively such that $U_R = \sqrt{u_R^2 + v_R^2}$. The expressions for u_R and v_R are given in (10)

$$u_R = \epsilon(1 - w)u' \times \sqrt{\eta \left(1 + \kappa \left(\sqrt{1 + 8 \frac{K_T}{\pi J^2}} - 1 \right) \right)^2 + (1 - \eta)} \quad (10a)$$

$$v_R = \gamma_R(v + r l_R) \quad (10b)$$

where l_R is the correction of flow straightening factor to yaw-rate, γ_R is the flow straightening factor of hull. η is the ratio of propeller diameter to the rudder height ($\eta = \frac{D_p}{h_R}$), ϵ is the ratio of wake fractions among rudder and propeller ($\epsilon = \frac{1-w_R}{1-w}$), $\kappa = \frac{k_x}{\epsilon}$ where k_x is the ratio of propeller stream on rudder.

All the rudder force parameters described above are listed in Table 5

TABLE 5: RUDDER FORCE AND MOMENT PARAMETERS

Parameter	Value
$\frac{A_R}{Ld}$	0.0182
t_R	0.258
a_H	0.361
x_H	-0.436
x_R	-0.5
l_R	-0.755
γ_R (starboard)	0.492
γ_R (port)	0.338
κ	0.633
ϵ	0.956
λ	2.164
η	0.7979

2.1.4 Coriolis forces and moments. The non dimensional Coriolis forces and moments about the midship frame of reference are given by (11)

$$X'_C = m'v'r' + m'x'_G r'^2 \quad (11a)$$

$$Y'_C = -m'u'r' \quad (11b)$$

$$N'_C = -m'x'_G u'r' \quad (11c)$$

2.1.5 Rudder angle variation. In this study, to account for rudder rate constraints to match practical scenarios the actual rudder angle δ is governed by a first order equation as shown in (12). Here δ_c denotes the commanded rudder angle. The actual rudder angle δ evolves slowly for a step change in commanded rudder angle δ_c . A lower value of T_R leads to a faster response time.

$$T_R \dot{\delta} + \delta = \delta_c \quad (12)$$

In addition, the rudder rate $\dot{\delta}$ is also saturated at $\dot{\delta}_{max}$. So the rudder-rate is given by:

$$\dot{\delta} = \begin{cases} \frac{\delta_c - \delta}{T_R} & \text{if } |\frac{\delta_c - \delta}{T_R}| \leq \dot{\delta}_{max} \\ \dot{\delta}_{max} & \text{if } \frac{\delta_c - \delta}{T_R} > \dot{\delta}_{max} \\ -\dot{\delta}_{max} & \text{if } \frac{\delta_c - \delta}{T_R} < -\dot{\delta}_{max} \end{cases} \quad (13)$$

In this study, the non-dimensional rudder time-constant T_R is taken as 1 and $\dot{\delta}_{max}$ is chosen as 5° per second for the full scale ship.

2.2 Abkowitz Model

The Abkowitz model [2] was proposed in 1964 in which a truncated third order Taylor series expansion is used to approximate the forces and moments acting on the ship. The expansion is taken about $u = U$, $v = 0$ and $r = 0$. Here U is the design speed of the vessel.

The 3 DOF non dimensional Abkowitz model is given by the following equations of motion :

$$\begin{bmatrix} m' - X'_{\dot{u}} & 0 & 0 \\ 0 & m' - Y'_{\dot{v}} & m'x'_G - Y'_f \\ 0 & m'x'_G - N'_{\dot{v}} & I'_{zz} - N'_f \end{bmatrix} \begin{bmatrix} \dot{u}' \\ \dot{v}' \\ \dot{r}' \end{bmatrix} = \begin{bmatrix} X' \\ Y' \\ N' \end{bmatrix} - \begin{bmatrix} X'_C \\ Y'_C \\ N'_C \end{bmatrix} \quad (14)$$

The superscript $(.)'$ represents dimensionless variables. m' and I'_{zz} denote the non dimensional mass and mass moment of inertia. x'_G is the position of centre of gravity in the longitudinal direction of body coordinate system (BCS). $\dot{u}'$, $\dot{v}'$, $\dot{r}'$ denote the non-dimensional accelerations in the surge, sway and yaw directions respectively. $X'_{\dot{u}}$, $Y'_{\dot{v}}$, Y'_f , $N'_{\dot{v}}$, N'_f are the non dimensional added mass coefficients.

Abkowitz model follows Prime I non-dimensionalization

where variables are defined as

$$\begin{aligned} m' &= \frac{m}{\frac{1}{2}\rho L^3} & x'_G &= \frac{x_G}{L} & \delta' &= \delta \\ \dot{u}' &= \frac{\dot{u}L}{U^2} & \dot{v}' &= \frac{\dot{v}L}{U^2} & \dot{r}' &= \frac{\dot{r}L^2}{U^2} \\ u' &= \frac{u}{U} & v' &= \frac{v}{U} & r' &= \frac{rL}{U} \\ X'_u &= \frac{X_u}{\frac{1}{2}\rho L^3} & Y'_v &= \frac{Y_v}{\frac{1}{2}\rho L^3} & Y'_r &= \frac{Y_r}{\frac{1}{2}\rho L^4} \\ N'_v &= \frac{N_v}{\frac{1}{2}\rho L^4} & N'_r &= \frac{N_r}{\frac{1}{2}\rho L^5} & I'_{zz} &= \frac{I_{zz}}{\frac{1}{2}\rho L^5} \end{aligned}$$

where ρ is the density of water, L is the ship length, U is the design speed of the ship.

The non dimensional external forces and moments acting on the vessel in surge, sway and yaw modes respectively are given by X' , Y' and N' and are expressed in the body coordinate system. The non dimensional Coriolis forces and moments are denoted by X'_C , Y'_C and N'_C and are computed as in section 2.1.4 including the added mass terms. The external forces and moments are expressed as a Taylor series in $\Delta u'$, v' , r' and δ as in (15), where $\Delta u' = u' - 1$.

$$\begin{aligned} X' &= X_0 + X'_u \Delta u' + X'_{uu} \Delta u'^2 + X'_{vv} v'^2 + X'_{rr} r'^2 + X'_{\delta\delta} \delta^2 \\ &+ X'_{v\delta} v' \delta + X'_{r\delta} r' \delta + X'_{uuu} \Delta u'^3 + X'_{vvu} v'^2 \Delta u' \\ &+ X'_{rru} r'^2 \Delta u' + X'_{\delta\delta u} \delta'^2 \Delta u' + X'_{uvr} \Delta u' v' r' \\ &+ X'_{u\delta} \Delta u' v' \delta' + X'_{ur\delta} \Delta u' r' \delta' + X'_{vr\delta} v' r' \delta' \end{aligned} \quad (15a)$$

$$\begin{aligned} Y' &= Y_0 + Y'_u \Delta u' + Y'_v v' + Y'_r r' + Y'_\delta \delta + Y'_{uu} \Delta u'^2 + Y'_{uv} \Delta u' v' \\ &+ Y'_{ur} \Delta u' r' + Y'_{u\delta} \Delta u' \delta + Y'_{vvv} v'^3 + Y'_{rrr} r'^3 + Y'_{\delta\delta\delta} \delta^3 \\ &+ Y'_{uuu} \Delta u'^2 v' + Y'_{uur} \Delta u'^2 r' + Y'_{uu\delta} \Delta u'^2 \delta + Y'_{vvr} v'^2 r' \\ &+ Y'_{vv\delta} v'^2 \delta + Y'_{rrv} r'^2 v' + Y'_{rr\delta} r'^2 \delta + Y'_{\delta\delta v} \delta'^2 v' \\ &+ Y'_{\delta\delta r} \delta'^2 r' + Y'_{vr\delta} v' r' \delta' \end{aligned} \quad (15b)$$

$$\begin{aligned} N' &= N_0 + N'_u \Delta u' + N'_v v' + N'_r r' + N'_\delta \delta + N'_{uu} \Delta u'^2 + N'_{uv} \Delta u' v' \\ &+ N'_{ur} \Delta u' r' + N'_{u\delta} \Delta u' \delta + N'_{vvv} v'^3 + N'_{rrr} r'^3 + N'_{\delta\delta\delta} \delta^3 \\ &+ N'_{uuu} \Delta u'^2 v' + N'_{uur} \Delta u'^2 r' + N'_{uu\delta} \Delta u'^2 \delta + N'_{vvr} v'^2 r' \\ &+ N'_{vv\delta} v'^2 \delta + N'_{rrv} r'^2 v' + N'_{rr\delta} r'^2 \delta + N'_{\delta\delta v} \delta'^2 v' \\ &+ N'_{\delta\delta r} \delta'^2 r' + N'_{vr\delta} v' r' \delta' \end{aligned} \quad (15c)$$

The hydrodynamic derivatives X'_u , Y'_v , Y'_r , N'_v and N'_r are assumed to be known beforehand for regression since these can be estimated with good accuracy through empirical methods or using panel methods. The values of these added mass derivatives are tabulated in Table 6

3. SYSTEM IDENTIFICATION

3.1 Data generation

Simulated trajectory data was generated using MMG model as described in section 2.1. The generated trajectory data consisted of standard maneuvers namely straight line maneuver, turning circle maneuvers for both port and starboard ($\delta = 35^\circ$), zig-zag

TABLE 6: KCS ADDED MASS COEFFICIENTS (1×10^{-5})

Added mass	Value
X'_u	-29.4
Y'_v	-732
Y'_r	-21
N'_v	-21
N'_r	-43

maneuvers which consisted of 10-35, 20-20 and 15-15 zig-zag maneuvers and both inward and outward spiral maneuvers. Surge velocity u , sway velocity v , yaw rate r and commanded rudder angle δ were sampled for each trajectory at 1 Hz dimensional time for a total of 3200 sample points for each trajectory. This data was used to predict the hydrodynamic coefficients present in Abkowitz model.

3.2 Formulation for regression

For system identification, the non-linear Abkowitz model described in section 2.2 is rewritten into a linear form with respect to the hydrodynamic coefficients as in (16).

$$A(k) \cdot X_c = (m' - X'_u) \dot{u}'(k) + X'_C(k) \quad (16a)$$

$$B(k) \cdot Y_c = (m' - Y'_v) \dot{v}'(k) + (m' x'_G - Y'_r) \dot{r}'(k) + Y'_C(k) \quad (16b)$$

$$C(k) \cdot N_c = (m' x'_G - N'_v) \dot{v}'(k) + (I'_{zz} - N'_r) \dot{r}'(k) + N'_C(k) \quad (16c)$$

The non dimensional accelerations $\dot{u}'(k)$, $\dot{v}'(k)$ and $\dot{r}'(k)$ are discretized and computed at sample times k using 5 point forward, central and backward differences. $[A, B, C]$ denote the parameter vectors and $[X_c, Y_c, N_c]$ are the coefficient vectors and are given by (17) and (18) respectively.

$$\begin{aligned} A(k) &= [1, \Delta u'(k), \Delta u'^2, v'^2, r'^2, \delta^2, v' \delta, r' \delta \\ &\Delta u'^3, v'^2 \Delta u' r'^2 \Delta u', \delta'^2 \Delta u', \Delta u' v' r' \\ &\Delta u' v' \delta', \Delta u' r' \delta, v' r' \delta]_{1 \times 16} \end{aligned} \quad (17a)$$

$$\begin{aligned} B(k) &= [1, \Delta u', v', r', \delta, \Delta u'^2, \Delta u' v', \Delta u' r', \Delta u' \delta \\ &v'^3, r'^3, \delta^3, \Delta u'^2 v', \Delta u'^2 r', \Delta u'^2 \delta \\ &v'^2 r', v'^2 \delta, r'^2 v', r'^2 \delta v', \delta'^2 r' + v' r' \delta]_{1 \times 22} \end{aligned} \quad (17b)$$

$$\begin{aligned} C(k) &= [1, \Delta u', v', r', \delta, \Delta u'^2, \Delta u' v', \Delta u' r', \Delta u' \delta \\ &v'^3, r'^3, \delta^3, \Delta u'^2 v', \Delta u'^2 r', \Delta u'^2 \delta \\ &v'^2 r', v'^2 \delta, r'^2 v', r'^2 \delta v', \delta'^2 r' + v' r' \delta]_{1 \times 22} \end{aligned} \quad (17c)$$

$$X_c = [X_0, X'_u, X'_{uu}, X'_{vv}, X'_{rr}, X'_{\delta\delta}, X'_{v\delta}, X'_{r\delta}, X'_{uuu}, X'_{vvv}, X'_{rrr}, X'_{\delta\delta\delta}, X'_{uvr}, X'_{uv\delta}, X'_{ur\delta}, X'_{vr\delta}]^T_{16 \times 1} \quad (18a)$$

$$Y_c = [Y_0, Y'_u, Y'_v, Y'_r, Y'_\delta, Y'_{uu}, Y'_{uv}, Y'_{ur}, Y'_{u\delta}, Y'_{vv}, Y'_{rrr}, Y'_{\delta\delta\delta}, Y'_{uuv}, Y'_{uur}, Y'_{uu\delta}, Y'_{vvr}, Y'_{vv\delta}, Y'_{rrv}, Y'_{rr\delta}, Y'_{\delta\delta v}, Y'_{\delta\delta r}, Y'_{vr\delta}]^T_{22 \times 1} \quad (18b)$$

$$N_c = [N_0, N'_u, N'_v, N'_r, N'_\delta, N'_{uu}, N'_{uv}, N'_{ur}, N'_{u\delta}, N'_{vv}, N'_{rrr}, N'_{\delta\delta\delta}, N'_{uuv}, N'_{uur}, N'_{uu\delta}, N'_{vvr}, N'_{vv\delta}, N'_{rrv}, N'_{rr\delta}, N'_{\delta\delta v}, N'_{\delta\delta r}, N'_{vr\delta}]^T_{22 \times 1} \quad (18c)$$

These hydrodynamic derivatives in (18) are obtained by solving (16) using regression techniques described further. It should be noted that this system of equations has many more equations than unknowns (hydrodynamic coefficients). Such a system is known as an over-determined system. The aim of system identification is to identify the solution that best fits the observed data and also captures the underlying physics of the system [14, 15].

3.3 Least Squares (LS) Regression

For overdetermined systems, least squares regression is used to find the set of parameters that minimizes the sum of the squares of the differences between the predicted values and the observed values. This difference is also termed as the residual sum of squares (RSS). The least squares solution for an overdetermined system can be found using (19)

$$x = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T \mathbf{b} \quad (19)$$

In this study, the $\mathbf{A}$ matrix from (19) corresponds to each of the equations in (17), and the corresponding $\mathbf{b}$ vectors are given by RHS of (16). The x vector consists of the desired hydrodynamic coefficients given in (18). The regression is performed in MATLAB and the regressed coefficients in the solution are then used to simulate the trajectories using (14).

3.4 LASSO regression

Lasso [16] is a type of linear regression that uses regularization and prevents over-fitting. The acronym “LASSO” stands for Least Absolute Shrinkage and Selection Operator. Lasso promotes sparsity by shrinking the coefficients to zero. This is achieved by including L1 regularization, which adds a penalty term proportional to the absolute value of the magnitude of coefficients to the loss function. The proportionality constant, also known as tuning parameter (λ) determines the strength of the penalty. Greater the value of the tuning parameter, more the coefficients are shrunk towards zero. The loss function in LASSO regression is given by (20)

$$\|\mathbf{Ax} - \mathbf{b}\|_2 + \lambda \|x\|_1 \quad (20)$$

where the number in subscripts denotes the norm which is considered. It is important to set the tuning parameter appropriately, as a larger value of λ can cause the model to underfit, and a smaller value can cause it to overfit. Cross validation is used to choose the optimal value of tuning parameter. The regression is performed in MATLAB with λ values varying in the range [0, 1]

and 10 fold cross validation is performed to choose its optimal value. The regressed coefficients in the solution are then used to simulate the trajectories using (14).

3.5 Support Vector Regression (SVR)

Support Vector Regression (SVR) can be used to solve the regression problem due to its high generalization and ability to find globally optimal solutions for higher dimensional data. In the case of non-linear data, the data points are mapped to a higher dimensional space using a kernel function. The data converted to a higher dimension can be fit using linear regression. For a given training data $[(x_1, y_1), \dots, (x_l, y_l)] \subset \mathcal{X} \times \mathbb{R}$, where $\mathcal{X}$ represents the input dimension the goal in ϵ -Support Vector Regression [17] is to find a function $f(x)$ that has at maximum ϵ deviation from the actual data and at the same time be as flat as possible.

The SVR hyperplane is defined by

$$y(x) = \mathbf{w} \phi(x) + b \quad (21)$$

where $\phi(x)$ is a feature corresponding to a kernel that transforms the given input data into a higher dimensional space to facilitate the separability of data. The optimization problem then becomes finding the minimum margin hyperplane that fits the transformed data in higher dimensional space. Flatness in the case of function described in (21) means minimizing the slope $\|\mathbf{w}\|$ of the function. Mathematically, this can be represented by a convex optimization problem as follows:

$$\begin{aligned} & \text{minimize} \quad \frac{1}{2} \|\mathbf{w}\|^2 \\ & \text{subject to} \quad |y_i - \langle \mathbf{w}, \phi(x_i) \rangle - b| \leq \epsilon \end{aligned} \quad (22)$$

It is assumed that the optimization is always feasible in (22). In other words, we will always be able to find a function that will satisfy (22). However, this may not be the case, and sometimes we may also want to allow for some errors. The optimization problem described in (22) can be modified with the help of slack variables $\zeta_i^{(1)}$ and $\zeta_i^{(2)}$ that denote the margins on both sides of the hyperplane respectively, as seen in (23).

$$\begin{aligned} & \text{minimize} \quad \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^l (\zeta_i^{(1)} + \zeta_i^{(2)}) \\ & \text{subject to} \quad \begin{cases} y_i - \langle \mathbf{w}, \phi(x_i) \rangle - b \leq \epsilon + \zeta_i^{(1)} \\ \langle \mathbf{w}, \phi(x_i) \rangle + b - y_i \leq \epsilon + \zeta_i^{(2)} \\ \zeta_i^{(1)}, \zeta_i^{(2)} \geq 0 \end{cases} \end{aligned} \quad (23)$$

The constant $C > 0$, also called the box-constraint in (23), is the regularization factor that determines the trade-off between the flatness of function y and the amount up to which the deviations larger than ϵ are tolerated. The effect of these constraints is similar to minimizing the ϵ -insensitive hinge loss function described in (24).

$$|\zeta|_\epsilon := \begin{cases} 0 & \text{if } |\zeta| \leq \epsilon \\ |\zeta| - \epsilon & \text{otherwise} \end{cases} \quad (24)$$

4. RESULTS AND DISCUSSION

Regression was performed as per the formulation mentioned in section 3.2 using the data generated for all the maneuvers as explained in section 3.1. The regressed non dimensional Abkowitz coefficients were obtained using the three techniques mentioned in section 3.3, 3.4 and 3.5. Table 7, 8 and 9 list the non dimensional Abkowitz model coefficients obtained from all three methods for surge, sway and yaw modes respectively. Figure 2 shows the comparison of trajectories obtained using the regressed Abkowitz coefficients for port side turning circle ($\delta = -35^\circ$) against the trajectory from MMG model simulation (Original). It should be noted that this trajectory was a part of the dataset used for finding the regressed coefficients. It can be seen that all three regression methods are able to recreate the trajectory used in system identification. However, it is interesting to note that the trajectory from coefficients identified using least squares regression yields the best match.

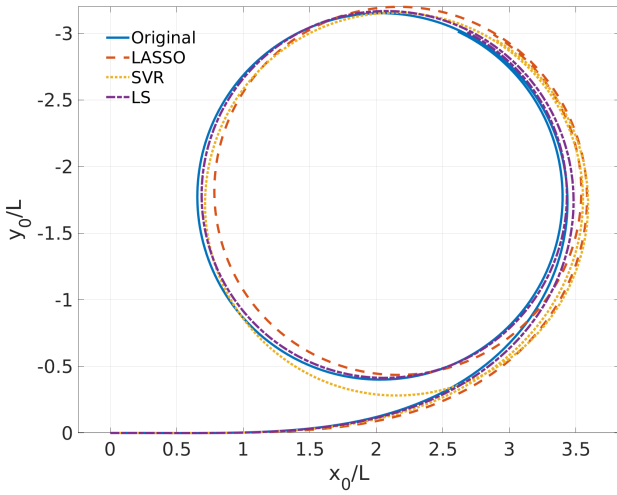


FIGURE 2: COMPARISON OF PORT SIDE TURNING CIRCLE ($\delta = -35^\circ$)

Figure 3, 4 and 5 show the comparison of trajectories obtained using the regressed Abkowitz coefficients for port ($\delta = -15^\circ$), starboard ($\delta = 15^\circ$) side turning circles and 10-10 zig-zag maneuver respectively against the corresponding trajectories from MMG model simulation (Original). These three trajectories were not included in the dataset used for predicting the hydrodynamic coefficients. Table 10 lists the mean errors computed as the mean of euclidean distance between the trajectories obtained using regressed coefficients and the corresponding MMG model trajectories.

For turning circle maneuvers, least squares regression approach provides the least mean error but for zig-zag maneuver it results in maximum mean error. This can also be observed from trajectories in Figure 5 where the least square regressed coefficients result in opposite direction turns in the zig-zag maneuver. This clearly demonstrates that least squares regression does not generalize well to trajectories not observed in the training data. The LASSO regressed coefficients seem to provide the best compromise in predicting the original trajectories not seen in training. However, further simulation tests are needed to verify

the performance over different types of trajectories.

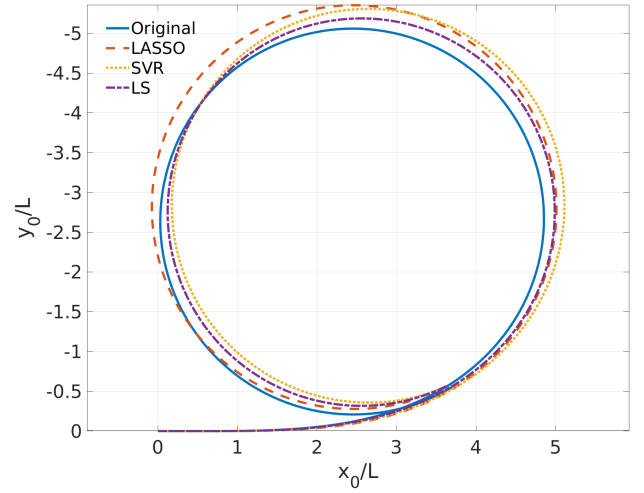


FIGURE 3: COMPARISON OF PORT SIDE TURNING CIRCLE ($\delta = -15^\circ$)

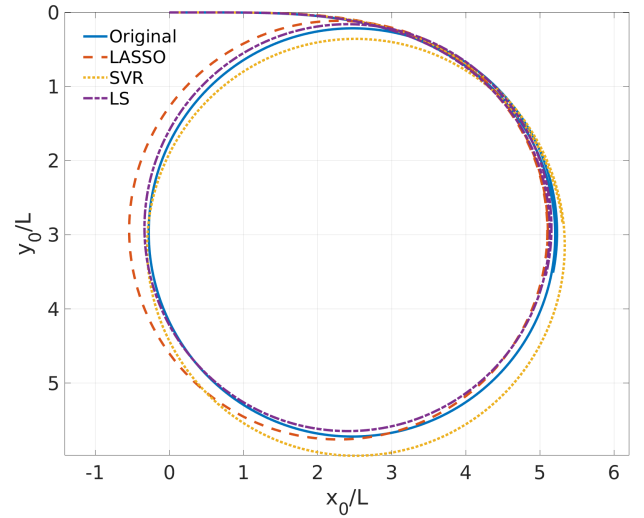


FIGURE 4: COMPARISON OF STARBOARD SIDE TURNING CIRCLE ($\delta = 15^\circ$)

5. CONCLUSION AND FUTURE WORKS

In this study, the non-dimensional Abkowitz model hydrodynamic coefficients were predicted for the KCS container ship using the data from simulated trajectories of MMG model derived from PMM tests. Three regression techniques namely, Least Squares, LASSO and Support Vector Regression (SVR) were used to predict these hydrodynamic coefficients. The trajectories obtained using these predicted coefficients were compared against the trajectories from the MMG model. Both SVR and LASSO regression were able to generalize well for trajectories not present in the dataset used for predicting the coefficients.

In further works, data collected from free running model experiments will be used instead of the MMG model simulation to predict the Abkowitz model coefficients for the KCS vessel. Other techniques such as Physics Informed Neural Networks (PINNs)

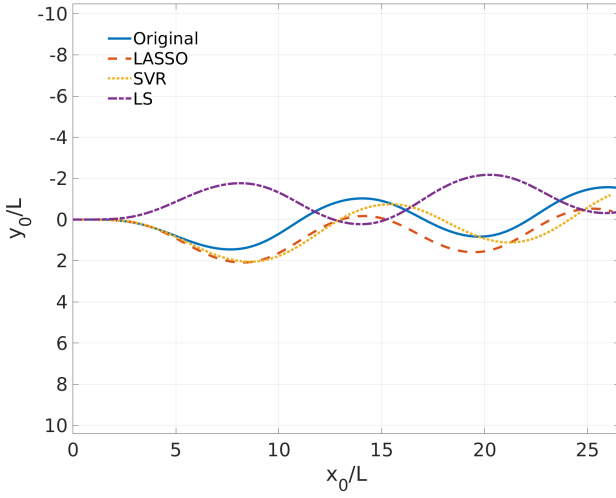


FIGURE 5: COMPARISON OF 10-10 ZIG-ZAG MANEUVER

TABLE 8: NON-DIMENSIONAL SWAY HYDRODYNAMIC DERIVATIVES FOR ABKOWITZ MODEL OF KCS VESSEL (1×10^{-5})

Coefficient	LS	Lasso	SVR
Y'_0	0.432	0	0
Y'_u	-22.115	0	36.966
Y'_v	-1257.569	-1590.432	-1001.523
Y'_r	263.464	0	194.471
Y'_δ	-246.062	-127.484	-154.339
Y'_{uu}	-28.985	0	-39.348
Y'_{uv}	8879.939	1708.672	1715.904
Y'_{ur}	3777.289	0	-138.955
$Y'_{u\delta}$	-1020.670	0	42.757
Y'_{vvv}	-199408.035	-29002.565	-16098.596
Y'_{rrr}	-8212.779	0.317	231.629
$Y'_{\delta\delta\delta}$	55.248	0	-20.124
Y'_{uuu}	5048.682	-7229.290	-1671.158
Y'_{uur}	6476.757	9.109	117.060
$Y'_{uu\delta}$	-2022.656	0	-4.423
Y'_{vvr}	-230252.527	0	3717.996
$Y'_{vv\delta}$	60670.839	0	-1456.984
Y'_{rrv}	-85809.497	0	-910.061
$Y'_{rr\delta}$	6135.945	0	-6.176
$Y'_{\delta\delta v}$	-4290.948	-113.294	-332.227
$Y'_{\delta\delta r}$	-894.971	20.488	70.174
$Y'_{vr\delta}$	43061.015	0	209.912

TABLE 9: NON-DIMENSIONAL YAW HYDRODYNAMIC DERIVATIVES FOR ABKOWITZ MODEL OF KCS VESSEL (1×10^{-5})

Coefficient	LS	Lasso	SVR
N'_0	-0.205	0	-0
N'_u	12.766	8.602	33.330
N'_v	292.766	659.168	442.322
N'_r	-215.660	-3.666	-115.281
N'_δ	120.743	64.013	89.578
N'_{uu}	18.290	13.266	76.968
N'_{uv}	-128.2294	252.146	531.208
N'_{ur}	-1152.418	0	-22.009
$N'_{u\delta}$	355.233	-20.723	-5.163
N'_{vvv}	71409.415	3118.513	4265.762
N'_{rrr}	2921.580	-54.930	-167.005
$N'_{\delta\delta\delta}$	-37.988	-27.271	-22.221
N'_{uuu}	-2524.594	42.914	-495.867
N'_{uur}	-1919.395	-214.859	-46.214
$N'_{uu\delta}$	687.726	10.758	-53.468
N'_{vvr}	82913.891	-617.431	-121.4650
$N'_{vv\delta}$	-22771.822	868.999	824.945
N'_{rrv}	30562.213	363.903	410.022
$N'_{rr\delta}$	-2241.106	0	-14.893
$N'_{\delta\delta v}$	1660.355	0	-83.393
$N'_{\delta\delta r}$	343.875	-0.00022421	-26.081
$N'_{vr\delta}$	-16052.721	0	-156.922

TABLE 7: NON-DIMENSIONAL SURGE HYDRODYNAMIC DERIVATIVES FOR ABKOWITZ MODEL OF KCS VESSEL (1×10^{-5})

Coefficient	LS	Lasso	SVR
X'_0	0	0	0
X'_u	-226.51	-217.29	-210.9
X'_{uu}	-50.81	-39.96	43.13
X'_{vv}	245.93	194.23	-53.97
X'_{rr}	-90.82	0	19.60
$X'_{\delta\delta}$	-186.48	-116.76	-133.20
$X'_{v\delta}$	123.22	-42.11	-78.17
$X'_{r\delta}$	197.15	0	9.01
X'_{uuu}	81.99	28.594	204.81
X'_{vvu}	-167.28	1258.80	25.13
X'_{rru}	-3.071	151.88	170.177
$X'_{\delta\delta u}$	-184.91	-0.68	-43.94
X'_{uvr}	-545.41	-464.02	-710.14
$X'_{uv\delta}$	13.61	332.65	37.08
$X'_{ur\delta}$	315.11	-129.28	-35.7
$X'_{vr\delta}$	-116.27	-121.25	-98.37

TABLE 10: MEAN DISTANCE ERROR BETWEEN TRAJECTORIES FROM REGRESSED COEFFICIENTS AND MMG MODEL SIMULATION

Trajectory	LS	Lasso	SVR
Port turning circle ($\delta = -15^\circ$)	0.2953	1.7859	0.5938
Starboard turning circle ($\delta = 15^\circ$)	0.1888	1.1736	2.0668
10-10 zig-zag maneuver	1.4989	0.7773	0.6252

will also be explored for predicting the hydrodynamic coefficients from experimental data.

ACKNOWLEDGEMENT

This work was partially funded by the Science and Engineering Research Board (SERB) India - SERB Grant CRG/2020/003093 and New Faculty Initiation Grant of IIT Madras. This work is also supported through the proposed Center of Excellence for Marine Autonomous Systems (CMAS), IIT Madras setup under the Institute of Eminence Scheme of Government of India.

REFERENCES

- [1] Mankabady, Samir. *The International Maritime Organization, Volume 1: International Shipping Rules* (1986).
- [2] Fossen, Thor I. *Handbook of marine craft hydrodynamics and motion control*. John Wiley & Sons (2011).
- [3] Yasukawa, Hironori and Yoshimura, Y. "Introduction of MMG standard method for ship maneuvering predictions." *Journal of Marine Science and Technology* Vol. 20 No. 1 (2015): pp. 37–52.
- [4] Abkowitz, Martin A. "Measurement of hydrodynamic characteristics from ship maneuvering trials by system identification." Technical report no. 1980.
- [5] Hwang, Wei-Yuan. "Application of system identification to ship maneuvering." Ph.D. Thesis, Massachusetts Institute of Technology. 1980.
- [6] Åström, Karl Johan and Källström, Claes G. "Identification of ship steering dynamics." *Automatica* Vol. 12 No. 1 (1976): pp. 9–22.
- [7] Jian-Chuan, Yin, Zao-Jian, Zou and Feng, Xu. "Parametric identification of Abkowitz model for ship maneuvering motion by using partial least squares regression." *Journal of Offshore Mechanics and Arctic Engineering* Vol. 137 No. 3 (2015).
- [8] Vijay, Aswin and Somayajula, Abhilash. "Identification of Hydrodynamic Coefficients using Support Vector Regression." *OCEANS 2022-Chennai*: pp. 1–7. 2022. IEEE.
- [9] Wang, Xue-Gang, Zou, Zao-Jian, Hou, Xian-Rui and Feng, XU. "System identification modelling of ship manoeuvring motion based on support vector regression." *Journal of Hydrodynamics, Ser. B* Vol. 27 No. 4 (2015): pp. 502–512.
- [10] Liu, B, Jin, Y, Magee, AR, Yiew, LJ and Zhang, S. "System identification of Abkowitz model for ship maneuvering motion based on ϵ -support vector regression." *International Conference on Offshore Mechanics and Arctic Engineering*, Vol. 58844: p. V07AT06A067. 2019. American Society of Mechanical Engineers.
- [11] Wang, Zihao, Zou, Zaojian and Soares, C Guedes. "Identification of ship manoeuvring motion based on nu-support vector machine." *Ocean Engineering* Vol. 183 (2019): pp. 270–281.
- [12] Fossen, Thor I. "Guidance and control of ocean vehicles." *University of Trondheim, Norway, Printed by John Wiley & Sons, Chichester, England, ISBN: 0 471 94113 1, Doctors Thesis* (1999).
- [13] Yoshimura, Yasuo, Masumoto, Yumiko et al. "Hydrodynamic database and manoeuvring prediction method with medium high-speed merchant ships and fishing vessels." *International MARSIM Conference*: pp. 1–9. 2012.
- [14] Di Mascio, Andrea, Dubbioso, Giulio, Notaro, Chiara and Viviani, Michele. "Investigation of twin-screw naval ships maneuverability behavior." *Journal of Ship Research* Vol. 55 No. 04 (2011): pp. 221–248.
- [15] Gibson, Scott B and Stilwell, Daniel J. "Hydrodynamic parameter estimation for autonomous underwater vehicles." *IEEE Journal of Oceanic Engineering* Vol. 45 No. 2 (2018): pp. 385–394.
- [16] Tibshirani, Robert. "Regression shrinkage and selection via the lasso." *Journal of the Royal Statistical Society: Series B (Methodological)* Vol. 58 No. 1 (1996): pp. 267–288.
- [17] Cortes, Corinna and Vapnik, Vladimir. "Support-vector networks." *Machine learning* Vol. 20 No. 3 (1995): pp. 273–297.