Adaptive Neural Tracking Control for an Autonomous Azimuthing Stern Drive (ASD) Tug

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Abstract. The ASD tug is considered the modern harbour tug due to its versatility in performing a wide variety of tugging/towing operations. With the advent of autonomous systems and desire to improve operations, there are benefits to automating the tug operations. Under different operating environments, there could be uncertainties in the model and the disturbance from the environment significant enough to affect the performance and control of the tug. In this paper, we consider the problem of tracking a desired trajectory for an autonomous ASD tug in the presence of uncertainties and unknown disturbances. The numerical modelling of an ASD tug based on a modified 4-DoF MMG model is first presented. The modified Maneuvering Modeling Group (MMG) model is then used to design a model based backstepping control. Thereafter, a adaptive neural network approximator is introduced which has the capability to account for uncertainties and unknown disturbance. The combination of approximation-based and backstepping design techniques allows us to handle time-varying model uncertainties. Stability analysis is carried out for the control design via Lyapunov analysis. Simulation are carried out for the tracking of maneuvering motion paths to demonstrate the performance of proposed approach.

1. INTRODUCTION
For future maritime autonomous surface ships (MASS), the on-board navigation and collision detection system require close to real-time projection of environmental influence on vessel behaviour in order to fill the role played by experience. This promotes the system-based manoeuvring models considering their rapid computational time despite the compromise on accuracy that sometimes must be made for long term trajectory forecasting. The most widely adopted models that are able to fulfil such requirements are, the Abkowitz model [1] based on truncated Taylor series, the Norrbin second order modulus model [2], and the modular-type model (MMG) which was recently standardised by the Japan Society of Naval Architects and Ocean Engineers [3]. When studying ship manoeuvrability in waves, the MMG model gains popularity since wave effect can be isolated from the hydrodynamic damping terms.

To allow the autonomous surface ships, to track a desired trajectory, the control system needs to be designed. Ship manoeuvring control systems need to cater for operating conditions and environment, such as inertia due to the massive structure, the hydrodynamics, wind, wave, current, and within the control design the parametric and functional uncertainties, un-modeled dynamics [4, 5]. On these challenges, a number of control approaches have been proposed with significant results achieved, such as classical Proportional-Integral-Derivative (PID) control [6, 7], Linear Quadratic Gaussian (LQG) control [8], $H_{\infty}$ control [9, 10], Model Reference Adaptive Control [11], Feedback Linearization Control [12], Sliding Mode Control [13, 14]. For example, a direct feedback linearization based adaptive control was
proposed for automatic steering of ships [12] in which both coursekeeping and course-changing were considered.

In the control domain, the backstepping control design technique is a useful approach for a range of nonlinear systems [15]. For example, for ship steering, a nonlinear backstepping controller was designed in strict-feedback form [16] and further optimized using genetic algorithm [17]. To construct and apply the nonlinear backstepping control, accurate parameters and nonlinear functions of ship manoeuvring model are needed. By incorporating the Nussbaum-type gain into adaptive backstepping design, a robust controller was proposed for ship heading nonlinear system in the presence of unknown sign of uncertain control coefficients [18]. Later, this approach was extended to ship heading nonlinear system in the presence of uncertain control coefficients [19] as well as input saturation [20, 21].

For work with parametric uncertainties, adaptive neural network (ANN) control design becomes an advanced approach in dealing with the highly uncertain, nonlinear and complex systems [22]. Then, the minimal learning parameter (MLP) techniques was applied to control scheme [23] to reduce the number of design control parameters update online [24]. This elegant adaptive control scheme was extended to ship steering uncertain nonlinear system with rudder actuator dynamic [25]. In [26], a class of feedforward approximators was designed for planar control of surface vessels. Recently, a modified DSC approach and NNs based adaptive control scheme for steering system of a robotic unmanned surface vehicle (USV) with model uncertainties and measurement noises was proposed [27]. In addition, several adaptive NN control approaches were employed to carry out the simulation studies for ship steering systems [28, 29] recently.

Inspired by the above works, in this paper, the numerical modelling uses a modified 4-DoF MMG model to describe the manoeuvrability of a generic Azimuthing Stern Drive (ASD) tug developed at TCOMS. To extend beyond planar and steering type adaptive neural network control, we focus the control design on the 4-DoF ASD MMG type model developed. The contributions of this paper are:

- the 4DoF modeling of an ASD tugboat based on a modified MMG model.
- the design of a 4DoF model based control for the using a backstepping approach and
- the design of the 4DoF adaptive neural control for ASD type vessel which has the capabilities to account for uncertainties in the model and time varying disturbances

2. ASD TUG MODEL & COORDINATES
An example of a ASD tug is shown in Figure 1. Two right-handed coordinate systems are used in this study as shown in Figure 2. The local reference frame is represented as \((x, y, z)\) which moves along with the manoeuvring motion, and the origin is located at the centre of gravity (CoG). The global reference frame is denoted as \((x_o, y_o, z_o)\) and is fixed in the earth-fixed-frame. The two coordinate systems align at the initial instant and the global velocities of the vessel are related to the local velocities as

\[
\begin{align*}
\dot{x} &= u \cos \psi(t) - v \sin \psi(t) \\
\dot{y} &= u \sin \psi(t) + v \cos \psi(t) \\
\dot{\phi} &= p \\
\dot{\psi} &= r
\end{align*}
\]

where \(u, v, p\) and \(r\) are the surge, sway, roll angular and yaw angular velocity in the body-fixed coordinates of the vessel respectively. \(\phi\) and \(\psi\) as the roll and yaw angle in the earth-fixed coordinates of the vessel and \((\dot{\cdot})\) is the derivative of \((\cdot)\) with respect to time.

3. FORMULATION OF 4-DOF MANOEUVRING MODEL
Manoeuvring motions in this paper are represented by surge, sway, roll and yaw, where only low frequency disturbances are considered. In addition, the hydrodynamic forces acting on the ship are treated quasi-steadily. The 4-DoF manoeuvring model is written by the following equations of motion.
The subscripts $H$ and $T$ represent the hydrodynamic loads exerted on or generated from the bare hull and thrusters.

\[
\begin{align*}
(m + m_x)\dot{u} - mvr &= X_H + X_{T1} + X_{T2} + d_u \\
(m + m_y)\dot{v} + mur &= Y_H + Y_{T1} + Y_{T2} + d_v \\
(I_{xx} + J_{xx})\dot{\phi} &= m_x z_H ur - mgGZ(\phi) + K_H + K_{T1} + K_{T2} + d_p \\
(I_{zz} + J_{zz})\dot{\psi} &= N_H + N_{T1} + N_{T2} + d_r
\end{align*}
\]

(2)

where $m$ is the displacement of the vessel, $m_x, m_y$ are the added mass of the vessel, $J_{xx}, J_{zz}$ are the moment of inertia of the vessel, $I_{xx}, I_{zz}$ the added moment of inertia of the vessel, $GZ$ the hydro-static righting arm of the vessel, $d_u, d_v, d_p, d_r$ are exogenous disturbance due to the environment in surge, sway, roll and yaw DoF respectively.
3.1. HYDRODYNAMICS OF HULL

In Equation (2), the hull hydrodynamic loads \( (X_H, Y_H, K_H, N_H) \) are non-dimensionised by the Prime-system II \([30]\) with the following expressions:

\[
\begin{align*}
X_H &= \frac{\rho L T u^2}{2} R'(u) + \frac{\rho L T U^2}{2} X'_H(u', v') \\
Y_H &= \frac{\rho L T U^2}{2} Y'_H(u', r') \\
K_H &= \frac{\rho L^2 T U^2}{2} K'_H(v', r', p') \\
N_H &= \frac{\rho L^2 T U^2}{2} N'_H(v', r')
\end{align*}
\]

where \( R'(u) \) is the Calm water resistance coefficient, \( X'_H, Y'_H, K'_H \) and \( N'_H \) are the non-dimensionised surge, sway force and roll and yaw moment respectively. Expanding the non-dimensionised hull damping \( (X'_H, Y'_H, K'_H, N'_H) \) are expanded as Taylor series of \((u', v', r', p')\):

\[
\begin{align*}
R' &= X_0 + X_{uu} uu + X_{uuu} uuuu \\
X'_H &= X_{vv} vv' + X_{rr} r'r' + X_{vvv} vvv \\
Y'_H &= Y_v v' + Y_r r' + Y_{uv} u'v' + Y_{uvr} u'v'r' + Y_{urt} u't' \\
K'_H &= K_v v' + K_r r' + K_{uv} u'v' + K_{urr} u't' \\
N'_H &= N_v v' + N_r r' + N_{uv} u'v' + N_{urr} u't'
\end{align*}
\]

\[ (4) \]

\( r' \) is the on-dimensionalised yaw rate \( r' = r(L_{pp}/U) \), \( p' \) the non-dimensionalised roll rate \( p' = p(L_{pp}/U) \), \( u' \) the non-dimensionalised rate \( u' = u/U \) and \( U \) the resultant ship over water speed \((m/s)\). Terms such as \( (X_v, X_r, Y_v, N_r \text{ and etc}) \) are the so called hydrodynamic derivatives or manoeuvring coefficients. In the surge equation, even terms are dominant whereas for the sway and yaw functions, the odd terms are superior to other components. These parameters are initially generated from a series of quasi-steady manoeuvres with CFD virtual Planar Motion Mechanism computations.

**Assumption 1** Referring to \([31]\), the relation between the roll moment \( K \) and the sway force \( Y \) is assumed to be linear and is expressed as,

\[
\begin{bmatrix} K_v & K_r & K_{uv} & K_{vr} & K_{rrr} \end{bmatrix} = z_H \begin{bmatrix} Y_v & Y_r & Y_{uv} & Y_{vr} & Y_{rrr} \end{bmatrix}
\]

**Assumption 2** The exogenous disturbances \( d_u, d_v, d_p, \) and \( d_r \) are smooth functions, dependent on the states of the system \( x, y, \psi, u, v, p, r \) and time \( t \), and are bounded.

**Remark 1** Assumption 2 is reasonable since the disturbances from the environment acting on the tug changes with the states of the tug and the time-dependent component of the disturbance can be largely attributed to the exogenous effects of the environment, which have finite energy and, hence, are bounded.

4. MMG MODEL BASED AND ADAPTIVE NEURAL CONTROL DESIGN

Consider the multiple-input-multiple-output (MIMO) dynamics of the 4 DoF ASD tug defined in (1) and (2). Expressing the model as a concise state space model, we have

\[
\begin{align*}
\dot{\eta} &= J(\eta) v \\
M \dot{v} &= \Delta(\eta, v, t) + \tau + d(\eta, v, t)
\end{align*}
\]

(6)
where
\[
J = \begin{bmatrix}
\cos \psi & -\sin \psi & 0 & 0 \\
\sin \psi & \cos \psi & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1
\end{bmatrix}, \quad \Delta(\eta, v, t) = \begin{bmatrix}
X_H + m v r \\
Y_H - m v r \\
m_s z_H w r - m g T(\phi) + K_H \\
N_H
\end{bmatrix}
\]  

(7)

where \(J(\eta)\) is the Jacobian transformation matrix, \(M = \text{diag}[m + m_x, m + m_y, I_{xx} + J_{xx}, I_{zz} + J_{zz}]^T \in R^{4\times 4}\) the output \(\eta = [x, y, \phi, \psi]^T \in R^4\) are the Earth-frame positions, roll and heading, respectively; \(v = [v_x, v_y, v_\phi, v_\psi]^T \in R^4\) are the vessel-frame surge, sway, roll and yaw velocities, respectively; \(\Delta(\eta, v, t) \in R^4\) the hull hydrodynamics and coupling terms, \(d(\eta, v, t) = [d_u, d_v, d_p, d_r]^T \in R^4\) represents the unknown disturbance from the environment and can also be used to include un-modeled and uncertainties among others, \(\tau = [X_T1 + X_T2, Y_T1 + Y_T2, K_T1 + K_T2, N_T1 + N_T2]^T \in R^4\) is the vector of thruster signals.

Lemma 1 [32] For the continuous functions \(d_i(\eta, v, t) : R^4 \times R^4 \times R \to R, i = 1, 2, 3, 4\), there exist positive, smooth nondecreasing functions \(p_i(\eta, v) : R^4 \times R^4 \to R^+\) and \(q_i(t) : R \to R^+\) such that

\[
|d_i(\eta, v, t)| \leq p_i(\eta, v) + q_i(t)
\]

Lemma 1 allows one to separate the multivariable disturbance term \(d_i(\eta, v, t)\), for \(i = 1, 2, 3, 4\) into a bounding function in terms of \(v, \eta\), the internal states of the tug, and a bounding function in terms of \(t\), which generally includes exogenous effects and uncertainties.

The control objective is to ensure that all signals are bounded, while the output follows a desired term \(\bar{\eta}\), the internal states of the tug, and a bounding function in terms of \(\bar{\eta}\) for some \(\delta_\epsilon > 0\).

Assumption 3 For the time-dependent functions \(q_i(t), i = 1, 2, 3\), there exist constants \(\bar{q}_i \in R^+, \forall t > t_0\), such that

\[
\|q_i(t)\| \leq \bar{q}_i
\]

Assumption 4 For all \(t > 0\), there exists constants \(N_1, N_2 > 0\) such that \(\|\hat{\eta}_d(t)\| \leq N_1\) and \(\|\hat{\eta}_d(t)\| \leq N_2\).

Remark 2 Assumption 4 requires that the desired trajectory be sufficiently smooth to avoid actuator saturation induced by sudden jumps of tracking error due to discontinuous command inputs.

Lemma 2 [33] For bounded initial conditions, if there exists a \(C^1\) continuous and positive definite Lyapunov function \(V(x)\) satisfying \(\gamma_1(\|x\|) \leq V(x) \leq \gamma_2(\|x\|)\), such that \(\dot{V}(x) \leq -\rho V(x) + c\), where \(\gamma_1, \gamma_2 : R^n \to R\) are class \(K\) functions and \(c\) is a positive constant, then the solution \(x(t)\) is uniformly bounded.

4.1. ADAPTIVE NEURAL APPROXIMATORS

Function approximators can be represented as multilayer feedforward networks which may be nonlinearly- or linearly-parameterized. Examples of feedforward approximators include adaptive neural networks [22, 33, 34, 35] and adaptive fuzzy systems [36]. A class of linearly parametrized feedforward approximators used to approximate the continuous function \(f(Z) : R^d \to R\) may be represented as follows:

\[
f(Z) = W^T S(Z) + \varepsilon(Z)
\]

where the vector \(Z = [z_1, z_2, \ldots, z_q]^T \in R^d\) are the input variables to the approximator, \(S(Z) \in R^d\) is a vector of known continuous (linear or nonlinear) basis functions, \(W \in R^d\) is a vector of adaptable
weights, and $\varepsilon$ is the approximation error which is bounded over the compact set, i.e., $|\varepsilon(Z)| \leq \bar{\varepsilon}, \forall Z \in \Omega_Z$, where $\bar{\varepsilon} > 0$ is an unknown constant.

We consider a class of linearly parameterized feedforward approximators, which, according to the universal approximation property [15], can smoothly approximate any continuous function $f(Z)$ over a compact set $\Omega_Z \subset \mathbb{R}^q$ to arbitrary any degree of accuracy as

$$f(Z) = W^{*T} S(Z) + \varepsilon^{*}(Z), \quad \forall Z \in \Omega_Z \subset \mathbb{R}^q$$

(10)

where $W^*$ are the ideal constant weights in the output layer, and $\varepsilon^{*}(Z)$ is the approximation error for the special case where $W = W^*$. The ideal weight vector $W^*$, an artificial quantity required for analytical purposes, is defined as the value of $W$ that minimizes $|\varepsilon(Z)|$ for all $Z \in \Omega_Z \subset \mathbb{R}^q$, i.e.

$$W^* := \arg \min_{W \in \mathbb{R}^l} \left\{ \sup_{Z \in \Omega_Z} |f(Z) - W^{T} S(Z)| \right\}$$

(11)

Motivated by [36] the basis functions are defined by

$$s_i(Z) := \frac{\mu_i(Z)}{\sum_{j=1}^{N} \mu_j(Z)}, \quad \mu_i(Z) := \prod_{j=1}^{N} \nu_j$$

(12)

where $\nu_j$ is one of the three functions from the $j$ th set:

$$\nu_j = \begin{pmatrix} 1/ (1 + e^{a_{1j}(Z_j-b_{1j})}) \\ e^{-a_{2j}|Z_j-b_{2j}|^2} \\ 1/ (1 + e^{-a_{3j}(Z_j-b_{3j})}) \end{pmatrix}$$

(13)

such that each $\mu_i$ is composed of a unique combination of the functions from the $N$ sets. The constant parameters $a_{kj}$ and $b_{kj}$ are user-defined.

4.2. CONTROL DESIGN

Define error variables $z_1 = \eta - \eta_d$ and $z_2 = v - \alpha_1$ and consider Lyapunov function candidate $V_1 = (1/2)z_1^T z_1$. Differentiating $z_1$ with respect to time yields

$$\dot{z}_1 = J(\eta) (z_2 + \alpha_1) - \dot{\eta}_d$$

(14)

Noting the property $JJ^T = I$, and choosing the virtual control as

$$\alpha_1 = J^T(\eta) (\dot{\eta}_d - K_1 z_1)$$

(15)

where $K_1 = K_1^T > 0$, the time derivative of $V_1$ along (14) is given by

$$\dot{V}_1 = -z_1^T K_1 z_1 + z_2^T J(\eta) z_2$$

(16)

The first term on the right-hand side (RHS) is stabilizing, and the second term will be handled in the next step. next, differentiating $z_2$ with respect to time yields

$$\dot{z}_2 = M^{-1}(\Delta(\eta, \nu, t) + \tau + d(\eta, \nu, t)) - \dot{\alpha}_1$$

(17)
where \( \dot{\alpha}_1 = (\partial \alpha_1 / \partial \eta) \dot{\eta} + (\partial \alpha_1 / \partial \dot{\eta}) \dot{\eta}_d + (\partial \alpha_1 / \partial z_1) \dot{z}_1 \). Consider the Lyapunov function candidate

\[
V_2^* = V_1 + (1/2)z_2^T M z_2. \]

From Lemma 1, Assumption 2 and 3 we have the following:

\[
\dot{V}_2^* \leq \begin{align*}
- z_1^T K_1 z_1 + z_2^T M z_2 \ + & \ z_2^T \left( \Delta(\eta, \nu, t) - M \dot{\alpha}_1 + \tau \right) \\
+ & \ \sum_{i=1}^{3} |z_{2,i}| (p_i(\eta, \nu) + \tilde{q}_i) \quad (18)
\end{align*}
\]

Consider the following desired control law

\[
\tau^* = - J^T(\eta) z_1 - K_2 z_2 - \Delta(\eta, \nu, t) + M \dot{\alpha}_1 - \text{Sgn}(z_2) (p(\eta, \nu) + \tilde{q}) \quad (19)
\]

where \( \text{Sgn}(z_2) := \text{diag}[\text{sgn}(z_{2,i})] \), for \( i = 1, 2, 3, 4 \) with \( \text{sgn}(\cdot) \) as the signum function. Substituting (18) into (19) the latter can be rewritten as

\[
\dot{V}_2^* \leq - z_1^T K_1 z_1 - z_2^T K_2 z_2. \]

In the case where \( \Delta(\eta, \nu, t), p(\eta, \nu) \), and \( q(t) \) are all unknown, the model-based control law (19) is not feasible. To overcome this problem, we utilize adaptive neural control to estimate the unknown entities in the control law as follows:

\[
\tau = - J^T(\eta) z_1 - K_2 z_2 + \tilde{W}^T S(Z) \quad (20)
\]

\[
\tilde{W}_i = - \Gamma_i \left( S_i(Z) z_{2i} + \sigma_i \tilde{W}_i \right) \quad (21)
\]

where \( \tilde{W} := \text{diag} \left[ \tilde{W}_1^T, \tilde{W}_2^T, \tilde{W}_3^T, \tilde{W}_4^T \right] \) contains the approximation weights, \( S(Z) = [S_1^T(Z), S_2^T(Z), S_3^T(Z), S_4^T(Z)]^T \) are the basis functions and \( \sigma_i \) is a positive constant. The neural network \( \tilde{W}^T S(Z) \) approximates \( W^*^T S(Z) \) defined by

\[
W^*^T S(Z) = \Delta(\eta, \nu, t) + M \dot{\alpha}_1 - \text{Sgn}(z_2) (p(\eta, \nu) + \tilde{q}) - \varepsilon(Z) \quad (22)
\]

where \( \varepsilon(Z) \in R^4 \) is the approximation error, \( \text{Sgn}(z_2) := \text{diag}[\text{sgn}(z_{2,i})] \), for \( i = 1, 2, 3, 4 \) with \( \text{sgn}(\cdot) \) as the signum function, \( Z = [\eta^T, \nu^T, \alpha_1^T, \dot{\alpha}_1^T]^T \) are the input variables to the feedforward approximators, and \( z_{2,i} \in R \) for \( i = 1, 2, 3, 4 \) are the elements of \( z_2 \).

Consider the augmented Lyapunov function candidate

\[
V_2 = V_1 + (1/2)z_2^T M z_2 + \frac{1}{2} \sum_{i=1}^{3} \tilde{W}_i^T \Gamma_i^{-1} \tilde{W}_i \quad (23)
\]

where \( \tilde{W}_i := \tilde{W}_i - W_i^* \). Differentiating \( V_2 \) along (14), (17) and (21) yields

\[
\dot{V}_2 \leq - \rho_l V_2 + C \quad (24)
\]

\[
\rho_l := \min \left( 2 \lambda_{\text{min}}(K_1), \frac{2 \lambda_{\text{min}}(K_2 - \frac{1}{2} I_{3 \times 3})}{\lambda_{\text{max}}(M)} \min_{i=1,2,3,4} \left( \frac{\sigma_i}{\lambda_{\text{max}}(\Gamma_i^{-1})} \right) \right) \quad (25)
\]

\[
C := \frac{3}{2} \left( \|W_i^*\|^2 + \frac{1}{2} \|\varepsilon\|^2 \right) \quad (26)
\]

where \( \lambda_{\text{min}}(\cdot) \) and \( \lambda_{\text{max}}(\cdot) \) denote the minimum and maximum eigenvalues of \( \cdot \), respectively.
Theorem 1 Consider the tug dynamics (6) with Assumptions 3 and 4 under the action of control law (20) and adaptation law (21). Then, for each compact set \( \Omega_0 \), where \( (\eta(0), v(0), \tilde{W}_1(0), \tilde{W}_2(0), \tilde{W}_3(0), \tilde{W}_4(0)) \in \Omega_0 \), the trajectories of the closed-loop system are semiglobally uniformly bounded. The tracking error \( z_1 \) converges to a compact set \( \Omega_{zs} := \{ z_1 \in \mathbb{R}^4 \mid \| z_1 \| \leq \sqrt{(2C/\rho_l)} \} \) asymptotically, where \( C \) and \( \rho_l \) are defined in (26) and (25) respectively.

Proof: From (24) and Lemma 1, it is clear that the signals \( z_1, z_2, \tilde{W}_1, \tilde{W}_2, \tilde{W}_3, \tilde{W}_4 \) are semiglobally uniformly bounded. From the boundedness of \( \eta_d \) in Assumption 2, we know that \( \eta \) is bounded. Since \( \dot{\eta}_d \) is also bounded, it follows that \( \alpha_1 \) is bounded, and in turn \( v \) is bounded. With \( W^*_i \) as a constant, we know that \( \tilde{W}_i \) is also bounded, for \( i = 1, 2, 3, 4 \). Therefore, all signals are bounded. To show that \( z_1 \) converges to \( \Omega_{zs} \) is straightforward using a similar approach as that found in [22].

5. SIMULATION RESULT

The physical geometry of the investigated generic ASD tug is developed as shown in Figure 1 and parameters in Table 1. For the hydrodynamic damping, the Taylor series of hydrodynamic damping forces and moments are ideal for small oblique flow angles \( 0^\circ < \beta < 30^\circ \) or \( 330^\circ < \beta < 360^\circ \) when the ASD tug advances forward. For operational conditions where \( \beta \) exceeds these ranges, the hydrodynamic damping can no longer be expressed in a concise mathematical formula. Therefore a database of \( (X, Y, K, N) \) was generated based on the quasi-static drift CFD simulations as given in Figure 3.

![Figure 3. HYDRODYNAMIC DAMPING AT DIFFERENT OBLIQUE FLOW ANGLES](image-url)

For control of the autonomous ASD tug, the control objective is to track the desired trajectory \( \eta_d(t) = [x_d(t), y_d(t), \rho_d(t), \psi_d(t)]^T \) where \( x_d(t) = (1)^\sqrt{2t} \) \( y_d(t) = \cos(xd(t)) \), \( \rho_d = 0 \) and \( \psi_d(t) = \)
Table 1. PHYSICAL PARTICULARS OF THE TCOMS G-TUG MODEL

| Scale | \( \lambda = 1.0 \) | \( \lambda = 9.78 \) | Scale | \( \lambda = 1.0 \) | \( \lambda = 9.78 \) |
|-------|----------------|----------------|-------|----------------|----------------|
| \( L_{pp} \) (m) | 33.0 | 3.37 | Thruster model | Ka 4-70 | Ka 4-70 |
| Beam (m) | 11.7 | 1.19 | Thrusters to keel (m) | 5.00 | 0.51 |
| Draft (m) | 4.80 | 0.49 | Thrusters lateral (m) | 5.20 | 0.53 |
| Disp. \( (m^3) \) | 825.6 | 0.88 | Blade dia. (m) | 2.20 | 0.22 |
| Ixx \( (kgm^2) \) | 180 | 0.89 | Pitch ratio | 0 | 0 |
| Izz \( (kgm^2) \) | 561 | 0.18 | Service cond. | 628.0 | |
| LCG (m) | 16.1 | 1.64 | Speed (m/s) | 6.68 | 2.14 |
| KG (m) | 4.80 | 0.49 | Blade rps | 4.8 | 15 |

The adaptive neural control (20) and adaptive law (21) are simulated with linearly parameterized basis function (12) in which \( \hat{W} = \text{diag}\left[\hat{W}_1^T, \hat{W}_2^T, \hat{W}_3^T, \hat{W}_4^T\right] \) are adaptable parameters, and \( Z = [\eta^T, \phi^T, \alpha_1^T, \alpha_1^T]^T \in \mathbb{R}^{16} \) are the inputs to the approximator. We choose \( \Gamma_1 = \Gamma_2 = \Gamma_3 = \text{diag}[5] \) and \( \Gamma_3 = \text{diag}[50] \), \( \sigma_i = 1 \times 10^{-6} \), \( K_1 = \text{diag}[10, 10, 5, 20] \) and \( K_2 = \text{diag}[30, 30, 5, 50] \). To evaluate the ability of the adaptive neural control to approximate the hull hydrodynamics, we set \( d_i(\eta, \nu, t) = 0, i = 1, 2, 3, 4 \). For comparison, we simulate the non-adaptive model-based control (19) without the signum function with \( K_1 = \text{diag}[5, 5, 3, 5] \) and \( K_2 = \text{diag}[5, 5, 5, 8] \). The initial conditions are \( \eta(0) = [0, 0, 5]^T \) and \( \nu(0) = [0.1, 0, 0, 0]^T \).

5.1. CLOSED LOOP PERFORMANCE

Figure 4 shows the tracking performance of both the non-adaptive model-based and adaptive neural control. It can be observed that the tracking performance of the tugboat is satisfactory for both controls. The states of the system for both control methods as compared to the desired are also shown in Figure 4. It is noted that the roll control command can be keep the ASD tug roll within certain range if roll parameter is included into the 4-DoF control design.

![Figure 4. TRACKING PERFORMANCE AND SYSTEM STATES COMPARISON](image-url)
From Figure 5, error signal $||z_1||$, it is observed that the model-based controller $\tau_{mb}$, performs better than the adaptive neural control. This is due to the complete knowledge of the hydrodynamics parameters which is utilized in the control strategy, with faster decay of tracking error and lower steady-state value. With time-varying disturbance, the adaptive neural is expected to perform better as the approximations can learn and compensate for the external disturbance $d(\eta, v, t)$ and will be treated in future work. The control commands $\tau_i$, $i = 1, 2, 3, 4$ are shown with the adaptive neural control commands having slight oscillations. The norm of all adaptive neural weights $||W||$ are observed to be bounded and stable. Hence, we can conclude that the adaptive neural design is stable and able to compensate for the dynamics of the 4-DoF ASD tug.

6. Conclusion
In this paper, the 4DoF model of an ASD tugboat based on a modified MMG model has been presented. The model-based tracking control has been designed using a backstepping approach. A stable adaptive neural feedforward network which has the capabilities to account for uncertainties in the model and time varying disturbances has been derived. It has been shown that the closed-loop signals under the proposed control are semiglobally uniformly bounded. Simulation results have demonstrated that the surface vessel is able to track a desired trajectory satisfactorily. This control method is applicable as one of the basic building block on tracking control for autonomous tugboats. As future work, the tug parameters generated from quasi-steady manoeuvres with CFD virtual Planar Motion Mechanism computations can be refined via model tests. This paper also builds the foundation for future extension of the work for azimuth thruster allocation with coupled roll and tracking control.

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