

SHIP PREDICTIVE CONTROL SYSTEM DESIGN BASED ON THE VESSEL DIGITAL TWIN

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ABSTRACT

Model Predictive Control (MPC) is defined as a model-based approach, thus necessitating the development of an internal predictive model, that is both reliable and realistic. It is not feasible to carry out this identification process on a real ship, due to the trials number and duration of each experiment. Moreover they are affected by the environmental disturbances that cannot be eliminated. Consequently, there is an imperative to identify a methodology for generating input-output data sets for the purpose of predictive model identification and validation. This paper details the development of a digital twin of a training ship, utilizing the mathematical model of the MMG (Mathematical Model Group). Following validation, the digital twin is employed as a source of input-output data for the model identification process. The paper goes on to describe the design of a ship predictive control system, starting from the initial idea and considering requirements, modelling and prediction, control signals computation, simulations and hardware-in-the-loop tests. The entirety of the research is grounded in the utilization of the Matlab software. The digital twin operates in real time as a component of the hardware-in-the-loop system, thereby addressing a current research gap and enhancing potential for the control quality in autonomous shipping predictive systems.



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1. INTRODUCTION

Digital twin is recognized as a virtual replica of a physical vessel, which may be updated in real time, using data coming out of her physical equipment. So, in autonomous shipping it plays crucial role and may be treated as a model cooperating with real twin, obtaining data from navigational systems, especially position, velocities, radar, lidar and sending prediction results to the control system or operator in Remote Operating Centre (ROC). This kind of concept is also useful in control system design, where digital twin is used as a situational part of system for motion prediction and as a

test-bed for model-based control synthesis. They are also used for automatic control system optimization and decision-making process enhancement in the field of autonomous shipping.

In shipping digital twins are gaining in importance and are being used increasingly in one of two areas: decision making and as a tool for system integration, testing and personnel training (Fonseca & Gaspar, 2021). As a decision support there are meant condition monitoring (Nejad et al., 2021), collaboration of simulation models based on real operational data and ship motion and fatigue estimation (VanDerHorn et al., 2022). Digital

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twin of the autonomous sailing vessel (ASV) should remain constantly synchronized in order to reproduce ship in a simulation environment as faithfully as possible. Autonomous vessel may be modelled as a neural network and trained using deep reinforced learning algorithms. In all of them vessel-specific support is provided, with the use of sensor-based data to update models. Made predictions are used to remain fatigue life. As a tool for system integration and personnel training – digital twin is used for control system emulation, compared with the hardware-in-the-loop testing (Zhang et al., 2022), where it gives integrated view on the vessel's various physical aspects, allows for control systems functional performance optimization. Thus, improving operational flexibility. It assists in daily operations and maintenance. Allowing for safe and easy data sharing between different ship modules and subsystems, what helps in fuel consumption prediction, travel planning and emissions calculation.

Berg and others in (Berg et al., 2025) present a concept of Nonlinear Model Predictive Control (NMPC) optimization based on reinforcement learning framework. Where NMPC parameters are tuned for peak performance of the controller with simultaneous unknown parameters identification carried out in real time.

Following the digital twin of the Gunnerus ship (Zhang et al. 2022) and model quality improvement connected with MPC parameters optimization (Berg et al., 2025), it was decided to create a similar digital-twin, linking both of the presented concepts. It was assumed that it will be used for the synthesis of a prediction control system for the Dorchester Lady training ship – LNG carrier model built in scale 1:24. To date, automatic control systems have been tested based on the system presented in (Rybczak & Rak, 2020). However, the need to synthesize a predictive control system, as presented in (Miller, 2023), has shown that there is a need for changes, allowing for coefficients of the nonlinear mathematical model of the ship online tuning, based on sensor data and accurate prediction of the ship's motion.

2. TRAINING SHIP DIGITAL TWIN

Real floating training ship – LNG carrier Dorchester Lady (Fig.1), built in scale 1:24 with kinematic and dynamic similarity and owned by Prof. Lech Kobylinski Foundation for Safety of Navigation, is used as a test bed for ship digital twin synthesis and operation. Training ship dimensions are presented in Table 1, compared to genuine ship. Used in the research LNG Carrier is 11.55 meters long, 1.8 meters wide and has a displacement of 8.21 tonnes. Large scale of the ship model, combined with real ship dynamics mapping, improves the quality of digital twin design and optimization, due to less susceptibility to disturbances than in studies with smaller ships' models operating in real conditions.

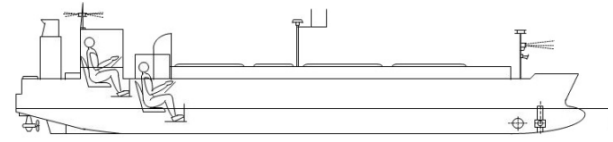


Figure 1. Training ship Dorchester Lady – LNG Carrier silhouette (Gierusz, 2016)

Table 1. Training and real ship dimensions

	Training ship	Real vessel
Length [m]	11.55	277.2
Breadth [m]	1.8	43.2
Draft [m]	0.5	12.0
Displacement [t]	8.21	113 500
Block coefficient C_B	0.78	0.78

Training ship Dorchester Lady is equipped with 2 azipods located on the aft and a bow thruster and rotatable bow thruster. This kind of electric propulsion allows for ship automatic control and autonomous navigation testing, ensuring sufficient manoeuvrability of the vessel. Usage of the bow thruster and rotational thruster is justified only when ships speed is less than 0.8 kt, which corresponds to speed of real ship equal to 4 kt. Speed is scaled according to the formula (1).

$$V_m = \frac{V_s}{\sqrt{\lambda}} \quad (1)$$

Where: V_m – ship's model speed, V_s – ship's speed, λ – model's scale.

When moving with speed higher than 0.8 kt training vessel becomes non-holonomic object. There are strong couplings between the longitudinal and angular velocities and the azipod set points. This phenomena makes difficult to steer without overshoot and oscillations, model ships' dynamics, update the internal digital twin model, and design control systems. Therefore there is a need to accurately model the ship's dynamics and to allow for the model coefficients updating in vessels digital twin.

We treat digital twin as a virtual object, working as a real time system, exchanging sensor data with real twin. It combines conventional simulations with real data on a separate platform, giving possibility of cyber-physical systems synthesis. Therefore, mathematical model of the vessel is the key issue in this concept. Nonlinear mathematical model, given by eq. (2) - (4), based on MMG model, presented in (Gierusz, 2016) was applied.

$$X_h = \frac{1}{2}\rho_w L T [X_{uu}u|u| + X_{vv}v^2 + L^2 X_{rr}r^2] + X_{vr}vr \quad (2)$$

$$Y_h = \frac{1}{2}\rho_w L^2 [Y_{vu}v|u| + Y_{vv}v|v| + L^2 Y_{ru}r|u| + L^2 Y_{rr}r|r| + L Y_{vr}v|r| + L Y_{rv}r|v|] \quad (3)$$

$$N_h = \frac{1}{2}\rho_w L^3 [N_{vu}v|u| + N_{vv}v|v| + L N_{ru}r|u| + L^2 N_{rr}r|r| + L N_{vr}v|r| + L N_{rv}r|v|] \quad (4)$$

Where: X^* , Y^* , N^* - denotes hydrodynamic coefficients for forces along x and y axes and moments around z axis respectively; u , v , r – ship velocities, L – ship length, T – draft and ρ_w - water density.

To ensure high fidelity of the predictive model, the hydrodynamics coefficients exhibiting the most significant impact on the longitudinal force (X_h), transverse force (Y_h), and yaw moment (N_h) are subjected to continuous online optimization. They are optimized using the Particle Swarm Optimization (PSO) method, based on sensor data. Ship longitudinal and transversal velocities are combined with rate of turn, ship course and position in the cost function, giving basis for optimization process. Cost function for the PSO algorithm defined as J_{PSO} is given by the equation (5). These decision variables are constrained by $\pm 50\%$ of their values relative to the coefficient derived from the model.

$$J_{PSO} = w_u(u - \hat{u}) + w_v(v - \hat{v}) + w_\psi(\psi - \hat{\psi}), \quad (5)$$

where: w_u, w_v, w_r, w_ψ denote the weighting parameters balancing the convergence across individual kinematic channels, adequate to longitudinal and transversal velocity and ships course. During each optimization cycle, the decision variables, representing the selected MMG model parameters variables are constrained by $\pm 50\%$ of their values relative to the coefficient derived from the model. Their nominal values are derived from prior hydrodynamic towing tank measurements or empirical formulas and by the physical quantities describing the ship model.

It was decided to build a digital twin based on a real-time computer. MMG mathematical model was applied and virtual interference allowing for model optimization was designed. A physical interface was built to enable communication with the controller, operating in a hardware-in-the-loop system. Depending on the deployment strategy, this system can be embedded directly onboard the vessel as part of an edge-computing setup or executed remotely within a Shore-based Remote Operating Centre (ROC).

2.1 Data sharing and model integration

The scheme of data sharing between digital and physical twins is presented in Fig.2. The data flow is structured as a closed-loop system operating in real time. On the right side of the diagram, the physical training ship *Dorchester Lady* continuously transmits its operational telemetry, including position given by GPS system, course and rate of turn delivered from gyrocompass, wind force and direction from ultrasonic anemometer and thruster setpoints to the digital twin platform. Digital twin is then used for implementation of continuous motion prediction and updates its internal state. Then it updates internal model and executes ship motion simulations, including trajectory tracking. Within this virtual environment, key

navigational metrics such as the Cross-Track Error (XTE) are computed relative to the planned route. These forward predictions are then processed by the model predictive control framework to synthesize optimal thruster action sequences. These forward predictions are then processed by the model predictive control framework to synthesize optimal thruster action sequences. As shown on the left side of Fig. 2, these commands are fed back to the physical ship via the Automatic Control block. This bidirectional exchange ensures continuous trajectory optimization, real-time disturbance attenuation, and precise maneuvering execution.

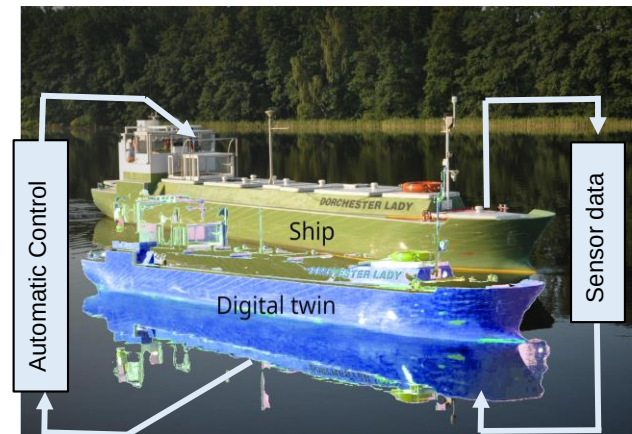


Figure 2. Dorchester Lady real and digital twins

The internal data architecture of the digital twin relies on a centralized repository designed for real-time telemetry logging, historical data management, and continuous playback of experimental sea trials performed on the physical vessel. The digital twin framework maintains uninterrupted read/write access to these storage repositories, enabling both online state estimation and offline model retraining.

The complete control synthesis, dynamic simulation, and signal processing pipeline are fully integrated within the MATLAB/Simulink ecosystem. Utilizing a unified software environment eliminates inter-platform compatibility issues, reduces data serialization overhead, and obviates the need for external hardware interfaces. Data communication between the physical ship's onboard systems, the digital twin, and the shore-based remote facilities is handled over a dedicated Transmission Control Protocol/Internet Protocol (TCP/IP) socket connection. This network bridge handles the deterministic exchange of control setpoints, multi-axis vessel motion variables (surge, sway, yaw), and environmental disturbances (such as wind speed and direction).

All measured state vectors and control signals are structured and saved as dynamic time-stamped structures (timeseries objects) within the local workspace. The architecture of the digital twin and the associated data flow network are schematically illustrated in Fig. 3. In

this diagram data lines, with their directions are marked by black solid lines. Dashed lines indicate data types, which are visualized on-board or in ROC. They serve as a source information for MPC controller and also, after visualization, may be used as a part of navigator's decision support system and for the purpose of autonomous ship remote pilotage and autonomous ship supervision. These visualized channels fulfill a dual operational role. They feed predictive trajectory projections directly into the MPC-LOS controller to execute autonomous track-keeping maneuvers. And they serve as an interactive decision support interface for human operators located on-board or within a Remote Operating Centre (ROC). This dual functionality supports advanced Maritime Autonomous Surface Ships (MASS) capabilities, including real-time situational awareness, remote pilotage, supervisory control, and post-mission telemetry data fusion.

This structure and data type allows for historical data readout, real-time sensor readout real-time sensor readout access, data fusion, usage and storage. Working on the heterogenous software eliminates the need of additional conversions and devices, which is very important during research and fast prototyping.

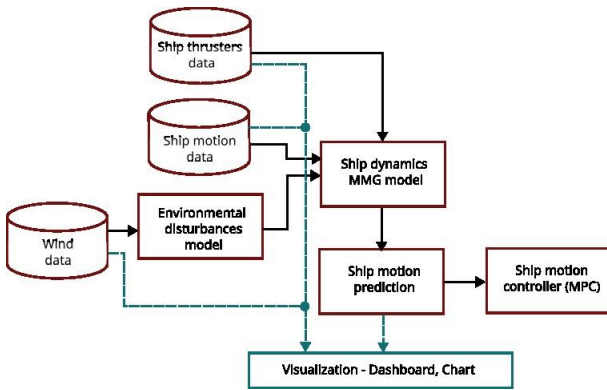


Figure 3. Digital twin's setup

2.2 MPC controller synthesis based on digital twin

In autonomous maritime navigation, high-precision trajectory tracking relies heavily on the continuous estimation and mitigation of the Cross-Track Error, which reflects the orthogonal deviation of the vessel's center of gravity from the nominal path segment defined by two successive waypoints (WPT_k and WPT_{k+1}). To address this challenge, the standard industry practice couples a trajectory guidance mechanism with a Line-of-Sight (LOS) path-following scheme, as originally conceptualized by (Fossen et al., 2003). The primary function of the LOS guidance algorithm is to convert geometric path deviations into a dynamically changeable reference heading (ψ_{LOS}) or reference rate of turn (r_{ref}). This conversion is governed by a lookahead distance parameter (Δ), which determines the convergence aggressiveness towards the desired path according to the kinematic relation given by eq. (6).

$$\psi_{LOS}(y_e) = \alpha_k + \arctan\left(-\frac{y_e}{\Delta}\right) \quad (7)$$

Where: y_e – denotes Cross-Track Error, computed based on the acquired real-time data when updating model or simulated position during Hardware in the Loop simulation, according to the usage of the digital twin.

Model Predictive Control (MPC) represents a modern, optimization-based control methodology that calculates sequences of future control inputs over a finite control horizon (N_u) by minimizing a predefined cost function across a prediction horizon (N). Building upon the structural framework proposed by (Miller, 2023), an integrated MPC-LOS guidance and control architecture (Fig. 4) was implemented in this study. Block diagram illustrates the cascaded MPC-LOS control architecture designed for autonomous ship trajectory tracking. The closed-loop control system operates through a sequential pipeline. The LOS module receives three waypoint coordinates ($WPT_{[3 \times 2]}$). First of them is one just passed, which forms with the next one trajectory tracking reference. Third one is used for the next turn angle estimation. Ship's current heading (ψ) and geographic position coordinates (x, y) are provided via primary feedback loops. Based on these inputs, the block calculates the target LOS heading angle (ψ_{LOS}) and the cross-track error (y_e). The calculated LOS heading (ψ_{LOS}) and cross-track deviation (y_e) are passed into the r mapping module. This block converts the trajectory guidance requirements into a target reference rate of turn (r_{ref}). MPC algorithm processes the reference rate of turn (r_{ref}) and compares it against the actual measured rate of turn (r) fed back from the vessel. Over a designated control horizon, the MPC solves an optimization problem to compute the optimal steering command. The control signal – azimuth angle of rotation (δ_z) is applied directly to the physical vessel or its digital twin model. The resulting motion outputs are continuously measured and fed back to the inner and outer guidance loops, ensuring accurate path following.

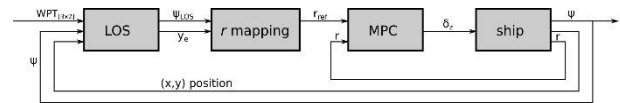


Figure 4. MPC_LOS concept schematic

A critical enhancement introduced in this research lies in the prediction mechanism. Conventional MPC implementations rely on a simplified, locally linearized state-space model embedded directly within the controller. While computationally lightweight, such linearized approximations fail to capture severe hydrodynamic nonlinearities, drift angles, and dynamic coupling between surge, sway, and yaw motions during sharp turning maneuvers. To overcome these fidelity constraints and achieve superior tracking accuracy, the conventional linear prediction engine was substituted with the online-calibrated digital twin. By utilizing this high-fidelity, non-linear replica for forward-in-time state

projections, the MPC algorithm generates highly optimal thrust setpoints (δ_z), thereby significantly reducing transient overshoot, damping cross-track oscillations, and enhancing trajectory tracking precision under varying environmental conditions.

Suboptimal control signals in control horizon (N_u) are computed using quadratic programming method, based on the cost function given by eq. (7).

$$J = \gamma_y \sum_{p=N_1}^N [r_{ref}(k+p|k) - r(k+p|k)]^2 + \gamma_u \sum_{p=0}^{N_u-1} [\Delta\delta_z(k+p|k)]^2 \quad (7)$$

where: γ_u, γ_y – output signal change and error weight coefficients, r_{ref} , r , $\Delta\delta_z$ – reference, output and control signal change values, $*(k+p|k)$ – signal value at $k+p$ time moment predicted in k time moment, N , N_u – prediction and control horizon lengths. Moreover, control signals – azimuth thruster angles of rotation are limited to ± 200 and their rate of change is constrained to ± 350 /s. Values of MPC controller coefficients are summed up in Table 2.

Table 2. MPC controller coefficients

Coefficient	Value
Output signal change weight (γ_u) [-]	0.1
Output signal error weight (γ_y) [-]	150
Prediction horizon length (N) [s]	15
Control horizon length (N_u) [s]	2

3. RESULTS

The experimental verification of the Dorchester Lady digital twin framework was conducted through a series of real-time lake trials to evaluate its online calibration and trajectory prediction capabilities under actual operating conditions. The initial experimental phase focused on evaluating the automatic online optimization algorithm responsible for identifying the hydrodynamic coefficients of the MMG mathematical model. Parameter identification was performed across a standardized suite of maritime maneuvering tests, including full-circle turning trials, acceleration-deceleration maneuvers, and the standard Kempf tests.

The first undertaken test verified the ability to automatically optimize the coefficients of the mathematical model. A direct comparative visualization of the vessel trajectories, contrasting the physical path recorded on the real training ship against both the uncalibrated (simulated) model and the PSO-optimized digital twin is depicted in Fig. 5. As illustrated, the uncalibrated model exhibits severe path deviation. They occur due to inaccuracies in baseline hydrodynamic coefficients. Following the online parameter

identification process, the optimized digital twin trajectory achieves high spatial alignment with the actual measured track. Quantitative metrics regarding the tactical diameter and circulation radius (r) across all three experimental conditions are presented in Table 3. Notably, the optimization process reduced the relative prediction error of the turning radius from an unacceptable 125.7% down to 32.3%, confirming the effectiveness of the proposed identification scheme.

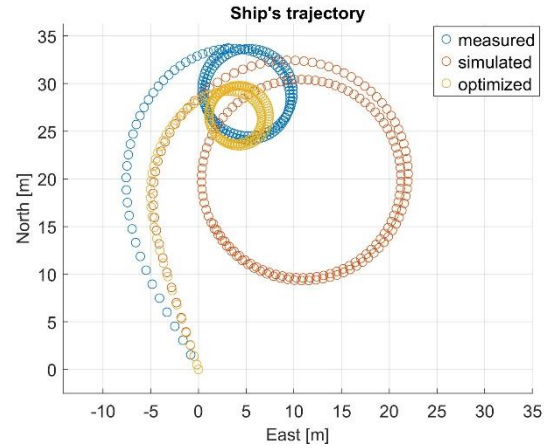


Figure 5. Real and digital twin trajectories

Fig.6 presents a multi-variable temporal comparison of the measured physical vessel dynamics against the uncalibrated and optimized digital twin outputs, spanning longitudinal velocity (u), transversal velocity (v), rate of turn (r), and absolute heading (ψ). The velocity profiles demonstrate that the online optimization successfully eliminates bias in the primary direction of motion. Specifically, near-perfect convergence is achieved for the longitudinal velocity (u), where the steady-state error drops to an almost negligible $\Delta u = 0.001$ m/s.

Conversely, the sway response exhibits a slight discrepancy, resulting in a steady-state transverse velocity error of $\Delta v = 0.12$ m/s. This discrepancy represents a drift speed modeling error equivalent to approximately 23% of the steady-state measured value. Such deviation is primarily attributable to complex, unmodeled hydrodynamic cross-flow forces and shallow-water effects acting on the hull during turning maneuvers. A comprehensive summary of the steady-state residual errors across all velocity channels ($\Delta u, \Delta v, \Delta r$) and trajectory radius errors (Δr) in meters is provided in Table 3.

Table 3. MPC controller coefficients

	r [m]	Δu [m/s]	Δv [m/s]	Δr [deg/s]	Δr [m]
Measured	4.67	0	0	0	0
Simulated	10.54	0.6	0.01	0.65	5.87
Optimized	3.16	0.001	0.12	0.47	1.5

The quantitative summary of the trajectory parameters and steady-state modeling errors is presented in Table 3. The data highlights a substantial improvement in accuracy achieved through the online optimization of the digital twin's mathematical model compared to the baseline simulation. The measured turning radius of the real training vessel is 4.67 m. The uncalibrated baseline simulation significantly overestimates this value at 10.54 m (representing a position error of $\Delta r = 5.87$ m). After online tuning, the optimized model reduces the radius to 3.16 m, bringing the absolute trajectory radius error down to $\Delta r = 1.5$ m. The steady-state error in surge speed is effectively eliminated by the optimization process. It was decreased from 0.6 m/s in the simulated model to an almost negligible 0.001 m/s in the optimized one. While the baseline simulation shows an artificially low sway error ($\Delta v = 0.01$ m/s) due to poor trajectory dynamic coupling, the optimized model stabilizes at $\Delta v = 0.12$ m/s. This residual error accounts for the unmodeled drift effects during steady turning. The steady-state error in yaw rate improves from $\Delta r = 0.65$ deg/s in the initial simulation to $\Delta r = 0.47$ deg/s following model calibration.

An evaluation was carried out to assess the quality of the predictive control improvement when replacing the conventional internal linear model with the calibrated digital twin within the MPC structure. Fig.7 illustrates the trajectory automatically tracked by the training ship across a pre-defined route consisting of multiple waypoints (red markers). A direct visual comparison is provided between the trajectory generated using digital-twin-based predictions (blue line), internal linear model predictions (purple line), and the reference path (orange dashed line). The performance differences between the two control approaches are prominently displayed during waypoint-passing and maneuver execution phases. When using the internal linear prediction model, the controller demonstrates notable phase lag and overshoot during course changes. This results in wide, sweeping maneuvers that deviate significantly from the straight-line legs connecting the waypoints. Training ship moves up to 15 m from the predefined path with oscillations, which is unacceptable in autonomous ship motion control, because it is not possible to determine whether a given trajectory is safe for the training ship. In contrast, the MPC coupled with the digital twin predictions, using non-linear MMG model, allows to initiate turns in the vicinity of the waypoints and realizes trajectory tracking without overshoot. The trajectory is traced as a curved path that follows the angle formed by successive segments of a straight-line trajectory (blue line). The digital twin-based prediction drives the vessel directly through the required waypoints, ensuring rapid convergence back to the nominal track following each course alteration. This optimization cuts down on unnecessary path elongation, resulting in a cleaner and more energy-efficient trajectory profile.

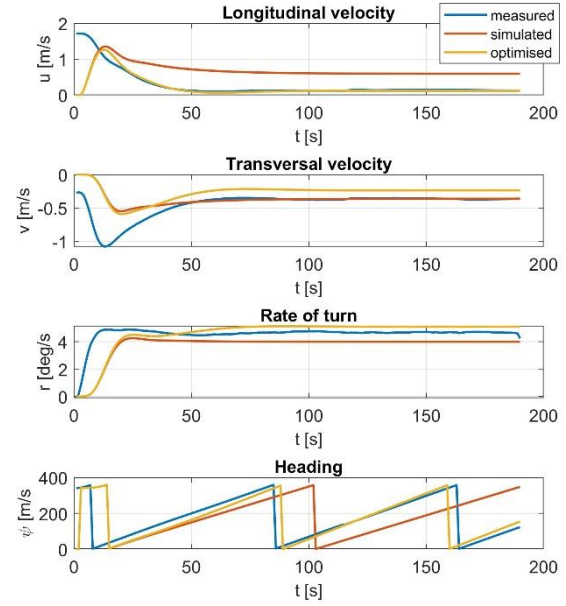


Figure 6. Real and digital twin velocities and heading

To quantitatively evaluate the trajectory-tracking performance of both predictive control schemes, the temporal response of the Cross-Track Error is illustrated in Fig.8. This plot compares the tracking deviation generated by the digital-twin-based MPC (blue line) against the internal linear model-based MPC (orange line) over the full maneuver duration. MPC controller based on the internal linear model exhibits pronounced XTE oscillations with higher amplitude variations. They range between -5 m and $+5$ m when moving along the straight line trajectory segment, e.g., around $t = 100$ s – 200 s. In contrast, the digital twin-based predictions based MPC controller effectively damps out cross-track oscillations, keeping XTE closely bounded near 0 m during straight-line path keeping.

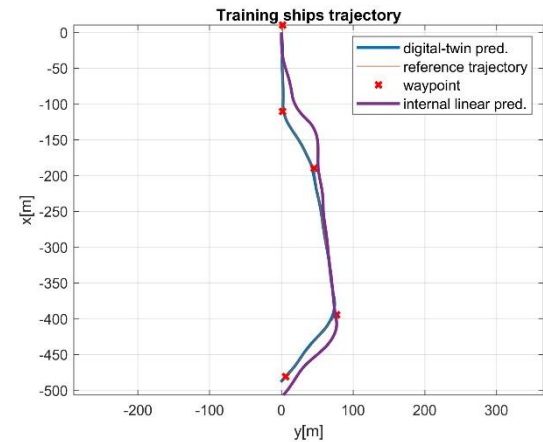


Figure 7. Training ship's trajectory



Figure 8. Training ship's cross-track error

Sudden discontinuities in XTE correspond to waypoint switching events, e.g. at $t \approx 50$ s. While both controllers experience peak deviations during sharp heading change, the digital twin-based scheme restores path alignment much faster. The rapid decay of the error curve after each peak demonstrates superior control responsiveness and transient recovery. In addition to achieving a 37% increase in overall path-tracking accuracy, the digital twin predictive controller optimizes the maneuver path execution. By accurately projecting nonlinear hydrodynamic forces during turns, the controller eliminates unnecessary path overshoot and control chatter, reducing the total mission completion time by approximately 80 seconds compared to the conventional internal linear model approach.

While the integrated MPC-LOS control framework working based on the online-calibrated digital twin demonstrates significant improvements in tracking fidelity, several physical and technical limitations must be addressed. First, the dynamic updating process of the MMG hydrodynamic coefficients via Particle Swarm Optimization (PSO) introduces a computational overhead that must be carefully managed to maintain real-time execution within strict sampling intervals. Second, the current implementation exhibits a residual steady-state transverse speed error ($\Delta v = 0.12$ m/s), which stems from complex, unmodeled hydrodynamic cross-flow forces, thruster interaction effects, and shallow-water disturbances during sharp turning maneuvers.

From a hardware-in-the-loop (HIL) perspective, the real-time interaction between the physical vessel sensors, digital twin, and the remote operating node relies heavily on deterministic network throughput. Any latency or packet loss occurring over the TCP/IP protocol can temporarily degrade state estimation accuracy. Future enhancements will focus on integrating Extended Kalman Filters (EKF) to compensate for sensor noise and network latency.

4. CONCLUSIONS

Conducted studies indicate the validity and necessity of creating digital twins for Maritime Autonomous Surface Ships (MASS). The digital twin serves as a core functional component within autonomous navigation architectures, providing high-fidelity, real-time motion predictions required for both shore-based remote pilotage from a Remote Operating Centre (ROC) and advanced model-based automatic control system synthesis.

By integrating online Particle Swarm Optimization (PSO) to continuously tune the hydrodynamic coefficients of the nonlinear MMG model based on live telemetry, the predictive capability of the system is substantially enhanced. The experimental verification performed on the real floating training ship physical model *Dorchester Lady* demonstrated that online parameter identification drastically improves trajectory prediction, reducing the relative error in circulation radius estimation from an initial 125.7% down to 32.3%. Furthermore, the steady-state surge velocity error was virtually eliminated, dropping to $\Delta u = 0.001$ m/s. The remaining sway velocity modeling error ($\Delta v = 0.12$ m/s, corresponding to approximately 23% of the measured steady-state value) highlights the ongoing challenge of capturing complex lateral drift dynamics and environmental cross-flow effects under physical trial conditions.

The main contribution of this work lies in replacing the conventional, internal linear prediction engine of the MPC controller with the online-calibrated nonlinear digital twin. This structural enhancement yielded a 37% overall increase in trajectory tracking accuracy compared to traditional linear MPC schemes. The digital-twin-driven controller effectively eliminated post-turn oscillations and transient overshoot, maintaining tight cross-track error bounds near 0 m along straight legs. Consequently, the vessel achieved faster track alignment following waypoint switching events, reducing the total mission completion time by approximately 80 seconds and optimizing energy consumption.

Future research will focus on developing adaptive, multi-objective optimization algorithms to further refine the lateral drift modeling. Additionally, expanding the digital twin's data repository architecture toward cloud-based servers with secure TCP/IP remote access will facilitate multi-vessel data fusion, extended Hardware-in-the-Loop (HIL) testing, and broader integration into fully autonomous commercial shipping networks.

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