SIMULATION AND APPLICATION OF MODEL-BASED AND MODEL- FREE TRACK CONTROLLERS FOR SHIP MANOEUVRING IN SHALLOW AND CONFINED WATER

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SUMMARY

If autonomous navigation in dense harbours and waterways will be made possible, knowledge on different domains will have to be incorporated. The paper presents a short background on model-based and model-free track controllers that are used for systematic research on the accessibility of ships in shallow and confined water. Both control methods were evaluated based on a simulation of a 110 m inland vessel at different loading conditions when navigating on the river Seine in Paris at different water levels, discharges and wind conditions. The model-based controller gives far more precise control in comparison with human controlled tracks on the same simulator platform than model-free controllers. Therefore, an investigation started on the use of multi-paradigm simulation methods that combine different training and validation platforms for model predictive reinforcement learning in, for example, path following. The principle of this methodology is shown in a simulation on the Western Scheldt and will be further investigated in the DDSHIP, Data-driven smart shipping, project.

NOMENCLATURE

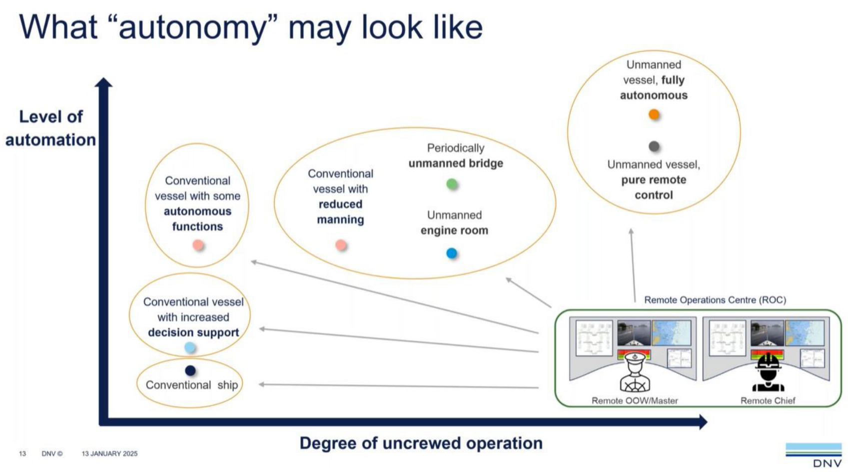
c	Weights of cost function aft, mid or fore (-)
e	(Cross track) Error (depending on parameter)
K	Proportional, integral and derivative gains of PID controller
mTEI	Mean track error integral (m)
MTE	Maximum track error (m)
mRI	Mean rudder integral (deg)
mRTV	Mean rudder total variation (deg)
mHEI	Mean heading error integral (deg)
T	Propeller thrust (N)
u	Longitudinal velocity (m/s)
v	Lateral velocity (m/s)
r	Yaw rate (deg/s or rad/s)
ξ	Look-ahead distance (time cycles in calculation)
η	Lateral deviation for cost function aft, mid or fore (-)
ψ	Heading (d = desired) (deg)
δ	Rudder angle (deg)

ABBREVIATIONS

AI	Artificial Intelligence
DOF	Degrees of freedom
FHSM	Flanders Hydraulics Simulator Matlab
LOS	Line of sight
MDP	Markov Decision Process
MPRL	Model Predictive Reinforcement Learning
NN	Neural Network
PMTC	Pre-science Model based Track Controller
RL	Reinforcement Learning

1 INTRODUCTION

Although, in Europe, not all waterways are yet open for remotely (human) controlled (inland) ships, research institutions and companies are joining efforts to investigate the challenges and possibilities for reliable path planning and path following by (model predictive) controllers. These controllers or autopilots can support different levels of autonomy as stated by CCNR (2022). Research is presently focusing on level 1 for steering automation, level 2 Partial automation for steering and propulsion control, and also level 3 systems with conditional automation to succeed in collision avoidance. High automation (level 4 with fallback performance without intervention of a boatmaster/skipper) and Autonomous or full automation (level 5 with unconditional performance without intervention) are not tackled yet.
Det Norske Veritas (DNV, 2025) presented during a webinar on January 14 2025 what "autonomy" should look like with systems in a two-dimensional field graded by the axes of "Level of automation" and "Degree of uncrewed operation" (Figure 1). The solutions on automation and crew reduction become larger so that depending on the economical and logistic operation of a ship and the available technologies a design can be chosen. In Flanders, conventional ships are upgraded with autonomous functions and decision support. Through the remote operations centres (ROC) (e.g. Shore control center from Seafar) inland and sea-going ships (FAST SIM from FastLines) are remotely controlled from the ROC with backup from the crew onboard. New ship designs are under investigation to combine the autonomy challenge with the zero-emission goals (X barge). With the timeline of the Japanese automation of ships set to 2040 (NIPPON Foundation), a more realistic time frame for developing trustworthy technologies for fully autonomous ships is introduced.



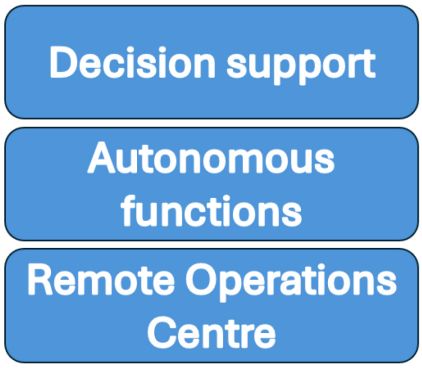


Figure 1 What "autonomy" looks like according to DNV (2025) (left) and the key elements in autonomous navigation (right).

The conditions in which ships operate differ, and in shallow and confined waterways with dense traffic the systems should be capable of interacting with the weather and waterway, other ships and constructions. An automated ship should set a preferred and continuously optimized path (planning) that considers the navigational parameters from the ship in the environment and follow that path (following) as accurately as possible with the propulsion and steering system.
Path planning and path following are closely connected because setting a path that a ship afterwards cannot follow, should be avoided by all means as controllers will not be capable of following the path.
The main focus of the paper is on path following with a predefined path based on knowledge of registered AIS tracks or human strategy. In open sea, the restrictions are due to the environmental constraints (wind, current, waves) and the closeness of ships towards each other in the waterway lanes, so that COLREGS (IMO) define the regulations to avoid collisions.
In shallow and confined water, restrictions in under keel clearance and lateral deviations occur due to the combination of bottom, banks and other shipping traffic in free-flowing or canalized rivers or canals, in open and sheltered wind areas. The use of predefined tracks is growing in inland navigation but these tracks are as smart as they represent a mean path of registered real ship tracks in very diverse circumstances (Potgraven, 2024). No local dynamic changes are automatically taken into account, so without observing the real situation a skipper, trusting the predefined track and the controller, can bring the ship in dangerous situations. The variability of tracks depends largely on the specific waterway dimensions in relation with the ship dimensions, the density of traffic and environmental conditions. Two examples are given based on profound AIS-analysis executed by Flanders Hydraulics in the framework of accessibility studies for the Flemish and Dutch Government (Verwilligen *et al.*, 2024a) and the Service Public de Wallonie (Verwilligen *et al.*, 2024b). In confined inland

waterways the ships are mainly sailing close to the centerline of the navigable section in both inbound and outbound directions and only for meetings or overtakings a two lane passage is organized. In Figure 2, this is shown based on an extensive AIS-analysis to investigate the traffic along the Walloon waterway network, with the red/orange (outbound) and greenish (inbound) tracks on the same path width at Péruwelz on the canal Nimy-Blaton-Péronnes.

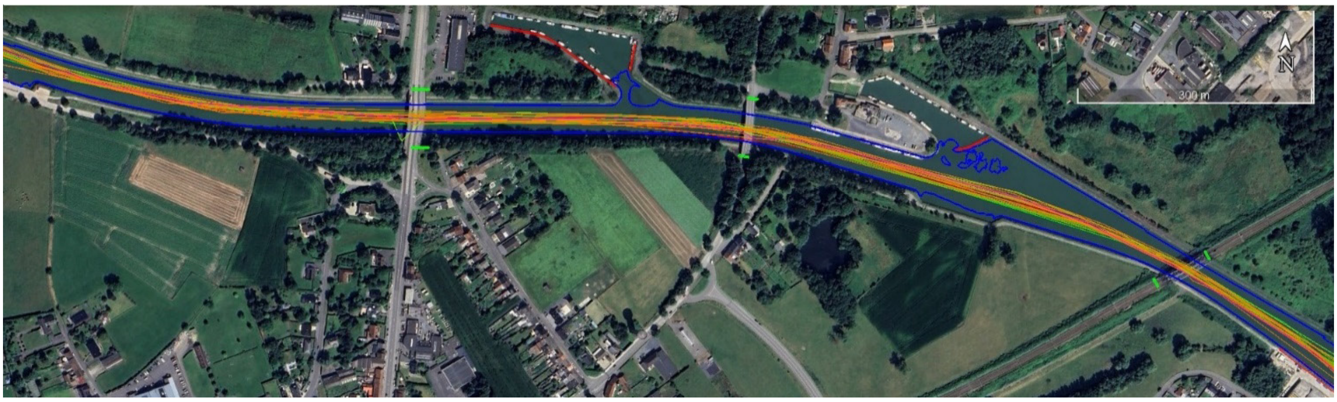


Figure 2 **Canal Nimy-Blaton-Péronnes at Péruwelz with inbound (greenish colour) and outbound (reddish colour) tracks of inland vessels (15-23/08/2022).**

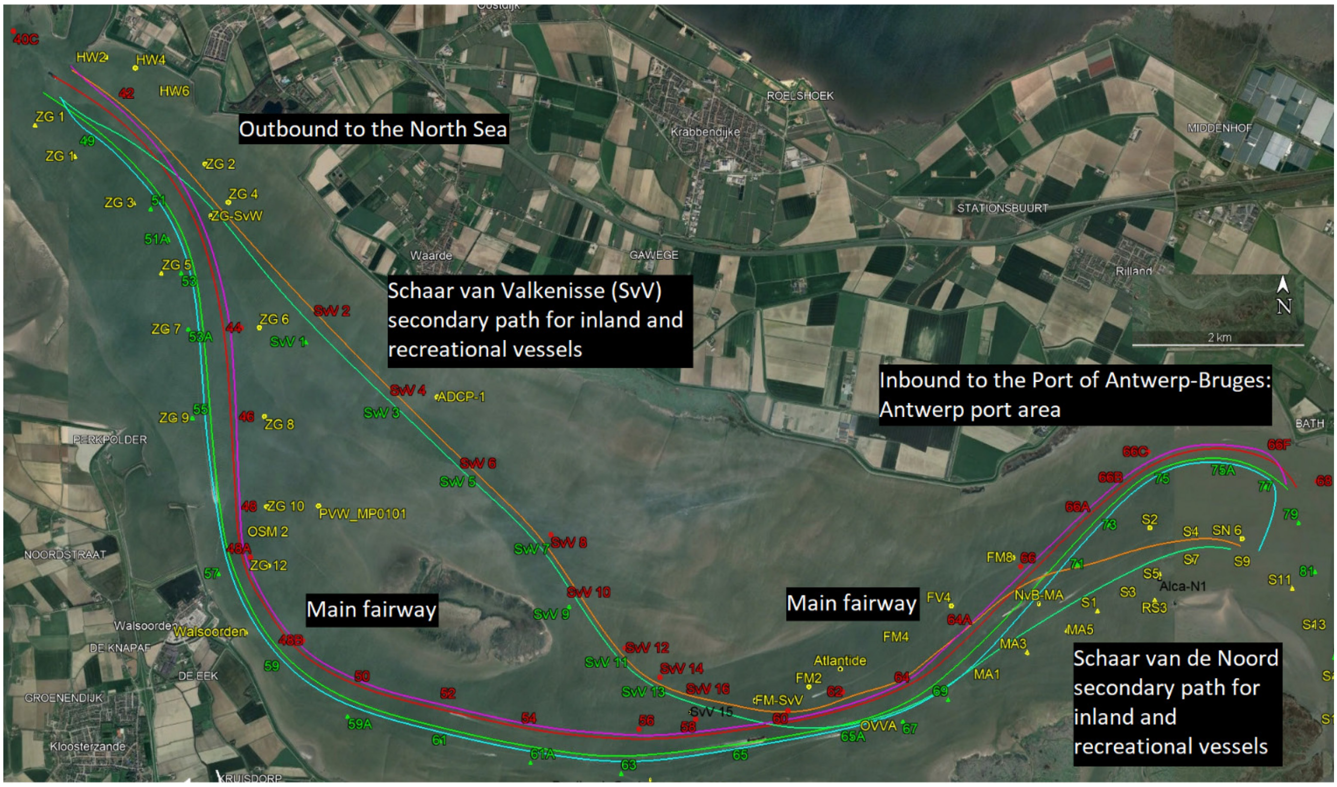


Figure 3 **Mean paths of sea-going (green = inbound, red = outbound) and inland (main fairway: blue = inbound, purple = outbound; secondary path: light green = inbound, orange = outbound) vessels on the Western Scheldt main fairway and secondary paths based on AIS-analysis (December 2013).**

On the Western Scheldt both sea-going and inland ships are operating. When both ship types are present in the main fairway, then ship waves of sea-going ships may hinder inland ships. On the other hand dedicated secondary paths (by-passes) for inland ships induce additional crossings of the main fairway with corresponding increased risk of collision. In Figure 3 the mean paths are shown for outbound (red=sea-going, purple=inland) and inbound (green=sea-going, blue=inland) vessels in the main fairway, and outbound (orange) and inbound (lighter green) inland vessels on the secondary paths of Schaar van Valkenisse and Schaar van de Noord. Two clearly distinctive lanes occur as the fairways with dense traffic require separate paths. The mean paths of the inland vessels in the main fairway are closer to the buoy lines than the sea-going (larger) vessels. Predefined tracks, designed based on these mean paths on two-way fairways or a centerline path (less ship-bank interaction) on inland waterways, require different design parameters for collision avoidance path planning and path following.

The research in this paper belongs partially to the joined project Data-driven Smart Shipping (DDSHIP) with the aim of setting a methodology for the development of model predictive reinforcement learned (MPRL) path planning and following (Flanders Hydraulics, University of Antwerp and Ghent University). For the training, simulation software of different institutes is interfaced so that a digital platform is developed which should not only serve research institutes but also companies willing to test their technologies like autopilots in virtual, representative environments.

2 CONTROLLERS IN SIMULATION

Flanders Hydraulics has a long experience in using a pre-science model based track controller (PMTC) for steering the design ship in diverse environmental conditions through manoeuvring simulations for port or waterway design. High-fidelity models are then available (derived from hundreds to thousands of model tests in a towing tank) that can accurately predict the ship behaviour in the confined waterway.
Nevertheless, for the majority of the vessels sailing worldwide and passing confined waterways, such advanced prediction models are lacking and only data (positional, kinematical and control) monitored while sailing can support the prediction. A demonstration of the use of different controllers from the PMTC to a fuzzy autopilot and thus model-based or model-free controllers was previously done for sea-going vessels in Chen *et al.* (2021) for the Western Scheldt and is now given for passages of the river Seine in Paris, a very confined river with nearby banks and more than 35 bridges of which 20 historical arch bridges. Considering the advantages of the fuzzy autopilot compared to the PMTC for the Western Scheldt, the question arises if model-free controllers suffice for confined inland waterways.

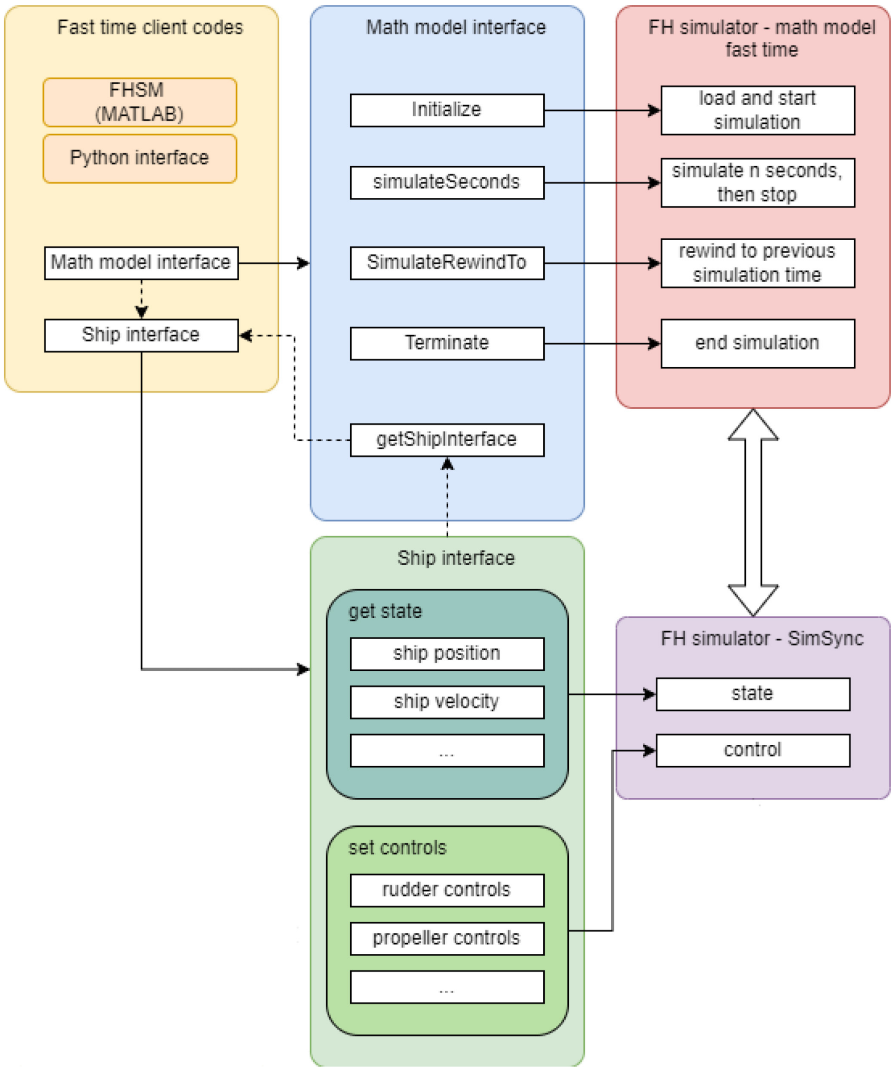


Figure 4 Interfacing between the external client codes and the simulator at Flanders Hydraulics.

2.1 INTERFACING SHIP MANOEUVRING MODELS AND CONTROL FOR SIMULATION

Flanders Hydraulics (FH) has several full mission bridge simulators specifically devoted to ship manoeuvring in shallow and confined water. At the heart of the simulators, mathematical manoeuvring models account for the forces related to shallow water, banks, ship - ship interactions, locks, waves, wind and current and nautical bottom. The simulators can now also serve as a virtual test bed for autonomous navigation by interfacing (third-party) controllers via newly developed software interfaces (Figure 4). The new interfaces, written in native C++ with a .NET wrapper to expose their functionality to a wider range of programming languages, provide control over the simulation (starting, pausing, rewinding, stopping), as well as the possibility to interact with SimSync, the communication layer of FH simulators. The interaction with SimSync provided by the new interfaces allows any client code to read ship state variables (e.g. the ship's position and velocity in 6DOF) and to change control values (e.g. propeller rate and rudder angle), thus making it possible to gain full control over a simulated ship. The new interfaces provide a reliable and practical way for client code to interact with both fast time and real time simulations, also decoupling the logic of the interface functionality from the implementation details of FH simulators.

2.2 MODEL-BASED TRACK CONTROLLERS

2.2 (a) Description

Model-based controllers are used in a wide range of disciplines. The models which are mathematical or data-driven, should describe the (physical) behaviour of the system that has to be controlled. In ship manoeuvring, model-based controllers are introduced to give more realistic control within the constraints of the ship in the environment. Mathematical models that are used at Flanders Hydraulics are at least 3 degrees-of-freedom (DOF) which describe the physical behaviour of the ship in the horizontal plane (surge, sway and yaw). But in control by non-nautical researchers, often lower DOF models are used. In the DDSHIP project researchers from different backgrounds are working together, which translates in the use of simplified 1 DOF (yaw) models up to 6 DOF complex modular models with all degrees of manoeuvring and sea-keeping (surge, sway, heave, roll, pitch, yaw) and separate modules to take into account the effects of hull, propulsion and steering but also the interactions between these modules.

2.2 (b) Pre-science model-based track controller or PMTC

The PMTC, which is a prescience model-based track controller developed at Flanders Hydraulics (Vantorre *et al.*, 1997), (Changyuan Chen *et al.*, 2021), is a model predictive controller (MPC) which uses high-fidelity mathematical models (Figure 5) not only for open water but also for other external hydrodynamic effects (e.g. ship-bank, ship-ship). The controller was first introduced in the 1990s to control ships under strong bank effects at the Canal Ghent-Terneuzen. The advantage is the accurate prediction rate but the drawback is that such models are not available for all ship types in all loading conditions and environmental circumstances, met in real life. The principle of adding different prediction models in a decision support system based on a cost function as Eq. (1) that minimizes the deviations (cross track errors) at fore, mid and aft of the ship contour compared to the reference track, can be used in simpler model-based controllers. The propulsion and steering system parameters (propeller rate and rudder angle for a conventional ship) are evaluated in the pre-science prediction phase so that the settings are chosen that minimizes the error from the reference track. The parameters that can be tuned, are the weights of the cost function c_F, c_M and c_A and the look-ahead distance ξ (Figure 5), together with the frequency and steps in which the propeller rate and rudder angle are changed to mimic the interval based settings by humans. This PMTC in prediction can be made as complex as necessary taken the ship and the waterway where the model-based control has to be executed. An investigation of the availability of different models in the prediction with some related accuracy has been conducted in Eloot & Mansuy, (2024). The exercise was made on the Seine in Paris and showed that some hydrodynamics (wind or ship-bank interaction) are more important than others for a specific control path.

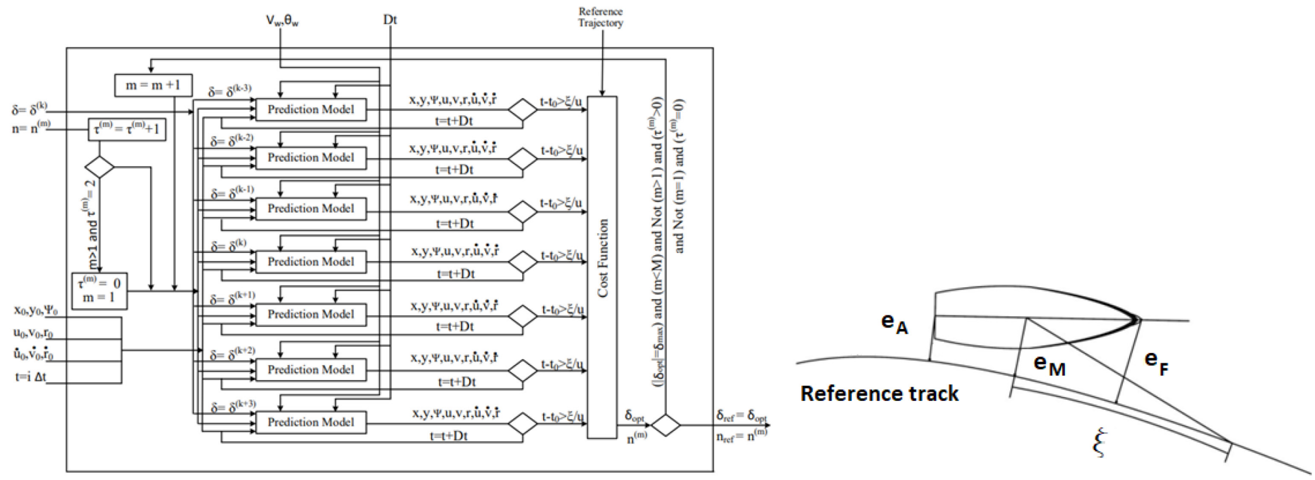


Figure 5 **Description of principle and cost function of pre-science model-based track controller or PMTC.**

$$C = c_F e_F^2 + c_M e_M^2 + c_A e_A^2 \quad (1)$$

2.2 (c) Model predictive reinforcement learning or MPRL

The DDSHIP research project, current state-of-the-art reinforcement learning (RL) algorithms are enhanced by incorporating model predictive control with domain-specific knowledge for collision avoidance and complex manoeuvring. This approach considers both data-driven and simplified manoeuvring models and is presented in Figure 6. In traditional RL, a deep neural network predicts the expected reward for each possible action given the current state, and the Markov Decision Process (MDP) selects actions based on a probability distribution of these expected rewards. The proposed enhancement combines this reward prediction with simulation-based validation. The key innovation is a two-stage process. First, a subset of actions with the highest predicted rewards are defined. Then, these actions are simulated over a predefined timeframe to recalculate their actual rewards. The MDP uses both the initial predictions and the simulation results to make final action selections, accounting for any discrepancy between predicted and simulated outcomes. This hybrid approach aims to leverage the strengths of both neural network predictions and physics-based simulations. Through this methodology, more reliable and safer decision-making in complex manoeuvring scenarios is expected to be achieved, while maintaining computational efficiency by limiting detailed simulations to the most promising actions.

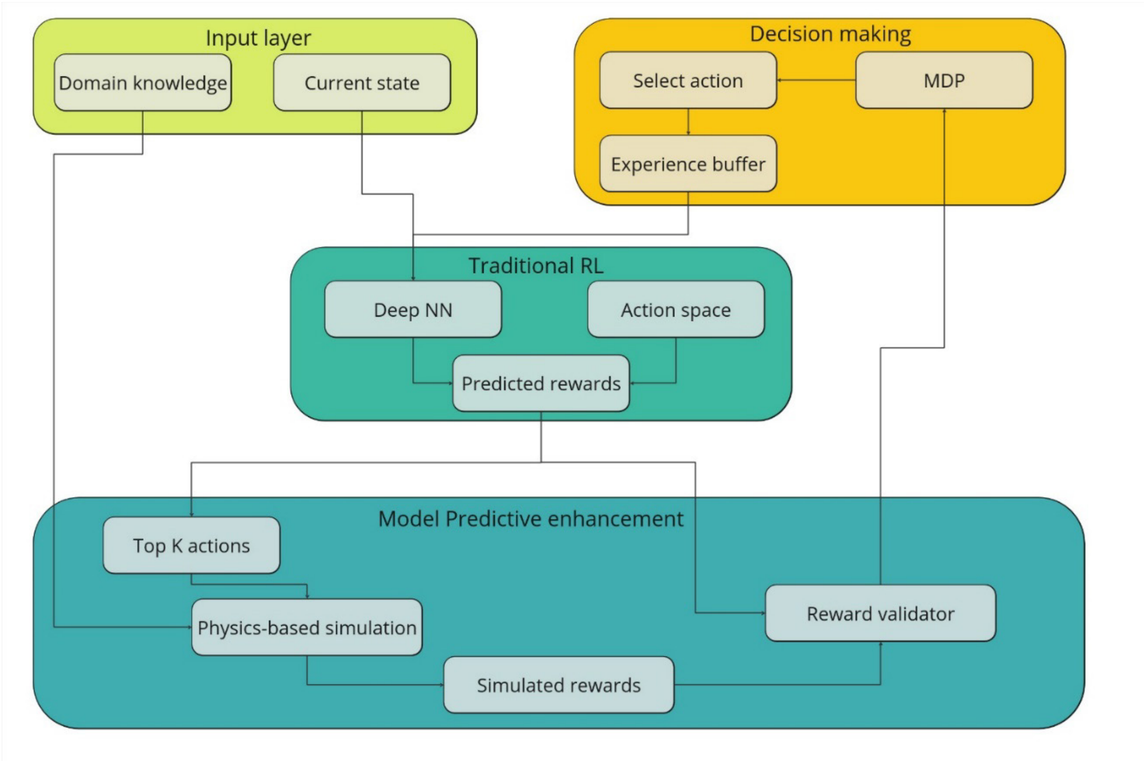


Figure 6 **Model predictive reinforcement learning flow chart with a decision making based on traditional predicted and physics-based simulated rewards.**

2.3 MODEL-FREE TRACK CONTROLLERS

For model-free track controllers errors comparing the actual and desired state are used for control decisions so that none of behavioral constraints are directly included in the decision process. In this research PID and Fuzzy controllers are used to compare the control with model-based controllers.

2.3 (a) PID controller

The proportional-integral-derivative (PID) controller is generally used in ship control. The error on the actual ψ and desired ψ_d heading angles, is evaluated and controlled by setting the rudder angle, depending on the proportional, integral and derivative gains K_P, K_I and K_D:

$$\delta = K_P(\psi_d - \psi) + K_I \int_0^t (\psi_d - \psi) d\tau - K_D \dot{\psi} \tag{2}$$

2.3 (b) Fuzzy controller

The Fuzzy controller which was elaborated and tested in the PhD work of Changyuan Chen (2021), Figure 7, consists of four blocks: fuzzification, fuzzy rules, fuzzy inference and defuzzification, to control an actual situation, described by a heading angle deviation e and the change in time of this deviation de/dt, through the setting of a rudder angle δ.

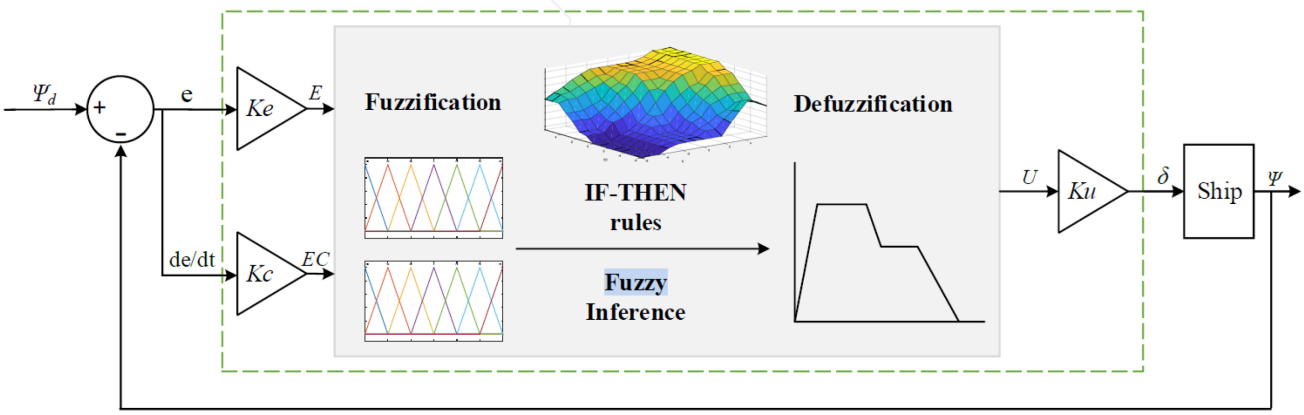


Figure 7 **Overview of the Fuzzy controller from Changyuan Chen (2021).**

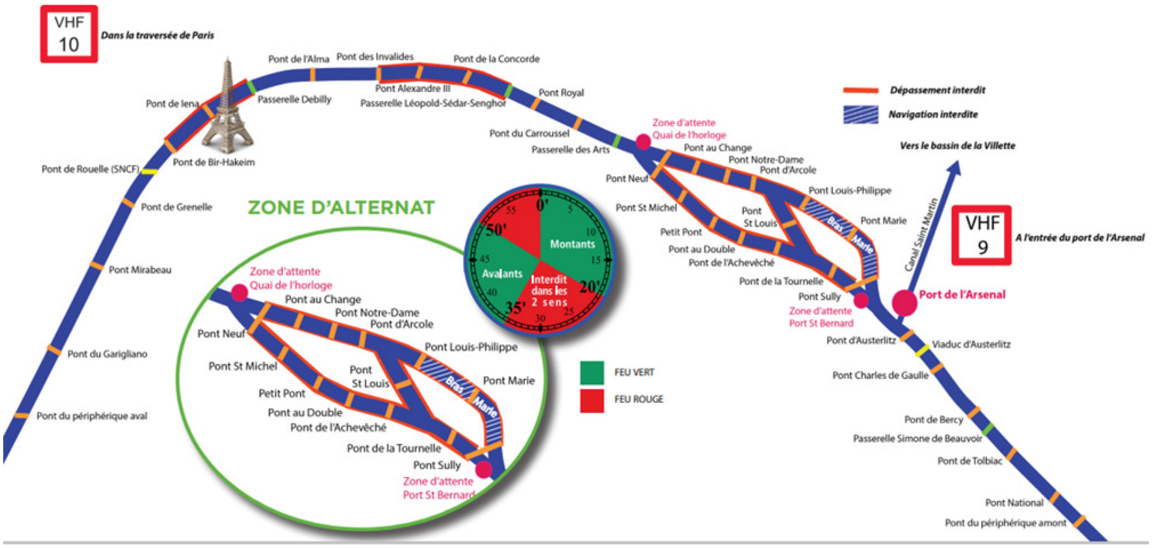


Figure 8 **Navigational procedures on the river Seine and the bridges in Paris (Voies Navigables de France).**

3 SIMULATIONS IN SHALLOW AND CONFINED WATER

To visualize the performance of model-based and model-free track controllers for manoeuvres in shallow and confined water an investigation is made for inland ships passing the city of Paris on the Seine and preliminary results for control through reinforcement learning for inland ships on the Western Scheldt in Belgium. The waterborne transport on the Seine is characterized by merchant ships bringing goods from inland Europe to the harbour of Le Havre and vice versa but in the meantime letting tourist enjoy the historic and modern scenery. The challenges are closely related to follow a path designed depending on the highly varying current, water level and wind conditions with restrictions due to the air draft and narrow width under arch bridges and alternate or dense traffic in different sections. The Western Scheldt is for inland ships much wider and thus the challenges are less so that this environment is taken for a proof of principle on reinforcement learning in autonomous navigation.

3.1 PASSING THE CITY OF PARIS ON THE SEINE

The use of the PMTC and model-free track controllers is demonstrated through the passage of the Seine for the alternate zone in Paris between Pont d'Austerlitz and Passerelle des Arts (Figure 8). The simulation environment was developed in the framework of an accessibility study for larger commercial and passenger ships (Marc Mansuy et al., 2023) under different discharges (water level and current) and wind conditions. Before executing real time simulations on a ship manoeuvring simulator with French professional skippers with ample experience on the river Seine, the trial matrix was reduced by executing fast time simulations with the PMTC as autopilot. A qualitative comparison between simulations with a human (skipper) and the PMTC was summarized in Eloot & Mansuy, (2024) and revealed good correspondence between the tracks realized by the high-fidelity PMTC and French skippers.

For the demonstration of the performance of model-based and model-free controllers a 110 m inland containership with a reduced beam of 10.55 m and two loading conditions of 1.7 m and 2.8 m are track-controlled on a predefined track at a water level of 120 cm at Pont d'Austerlitz, an increased current corresponding with 140 cm water level and a variable wind field of 2 to 4 Bft from a southwestern direction. Consecutively, as human controlled simulations from Marc Mansuy et al. (2023) were available, at an increased water level of 280 cm and corresponding current field, additional PMTC simulations were executed at this higher current. All conditions that are simulated with the ship and environmental parameters are summarized in Table 1.

Table 1 Ship and environmental parameters for the human, model-based and model-free controlled simulations (SIM, PMTC, FUZZY and PID).

Control/Simulation	Draft	Beam	Water level/current	Wind
Name	[m]	[m]	[cm]	[Bft]
SIM35, human	1.7	10.55	280/280	2-4
SIM36, human	1.7	9.65	280/280	2-4
PMTC0	1.7/2.8	10.55	120/140	2-4
FUZZY0	1.7/2.8	10.55	120/140	2-4
PID0	1.7/2.8	10.55	120/140	2-4
PMTC1	1.7	10.55	280/280	2-4
PMTC2	2.8	10.55	280/280	2-4
PMTC3	1.7	10.55	280/280	2-4
PMTC4	1.7	10.55	280/280	2-4

The predefined track was composed based on tracks sailed on the simulator during validation runs by French skippers and restrictions due to bridge passages. During real life sailing the skippers create margin in counteracting hydro- and a erodynamic influences by taking for example the inner bends of the zigzag manoeuvre to be executed between the islands on the Seine (Ile Saint-Louis and Ile de la Cité). Also the behaviour of the vessel itself, for example depending on the draft, has to be considered to safely pass and avoid under and above water collisions.

3.1 (a) Qualitative comparison

In the qualitative comparison the human and PMTC controlled simulations are first compared as both are considered as containing most knowledge based manoeuvring capacities. For the comparison two real time simulations (SIM35 and SIM36) were available executed by a French skipper but only at a larger water level of 280 cm and related current (Mansuy et al., 2023). An overall view is presented in Figure 9. The reference track for the controller is presented in light blue (with 0.1 km indication) and the PMTC simulation with blue filled black contours. A detail between 168.9 km and 170.3 km is shown in Figure 10 with an extraction of the passage of the bridges between 169.8 km and 170.3 km. All human and PTMC controlled ship tracks are free from depth lines (red at 1.7 m depth) and thus grounding but in SIM35 the skipper collided with the portside bridge pillar at Pont Neuf (170.3 km, red ship contour and green arch air draft). It can be seen on Figure 10 that the largest deviations are seen compared to the predefined track for SIM35 with continuous adjustments to keep back on track.

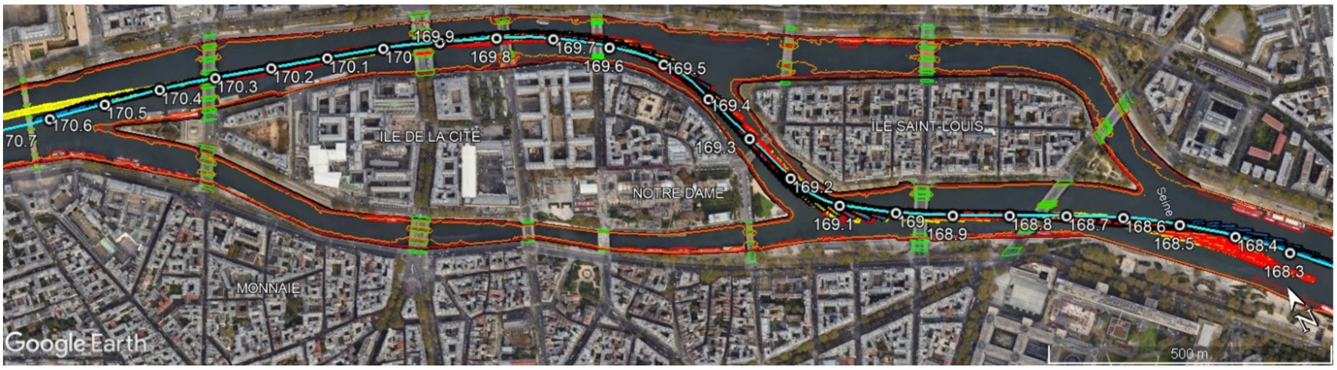


Figure 9 Overall view of the tracks of human (SIM35, SIM36) and PMTC0 simulations for a 110 m vessel at 1.7 m draft (120 cm water level, 140 cm current and SW 2 to 4 Bft wind) – km indication along the (light blue) preference track.

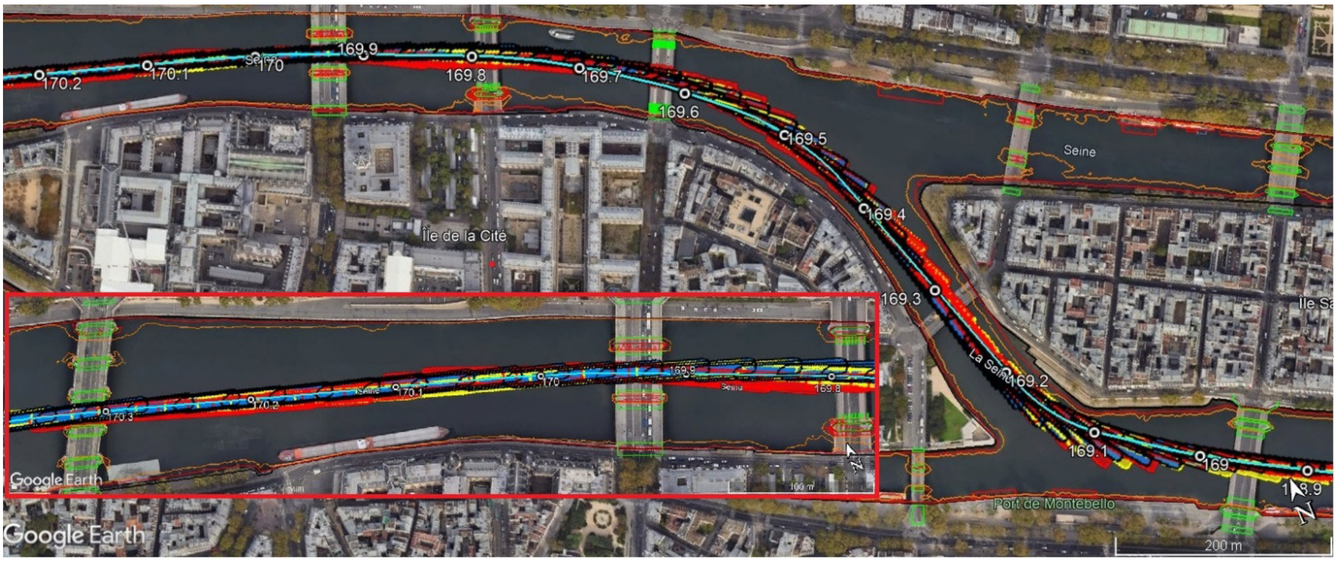


Figure 10 Detail of the zigzag manoeuvre between Ile Saint-Louis and Ile de la Cité with a closer view to the passages of the bridges between km 169.8 and 170.3 (blue with black contour = PMTC0, red = SIM35 and yellow = SIM36 by skipper).

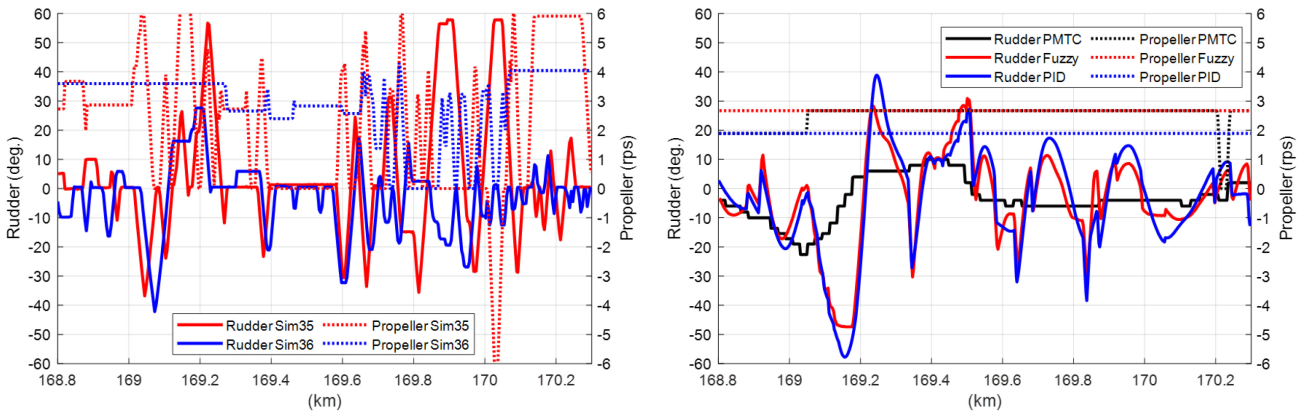


Figure 11 Use of rudder angle (deg) and propeller rate (rps) for human controlled (SIM35 and SIM36, left) and PMTC0, Fuzzy0 and PID0 simulations within the track between 168.8 and 170.2 km on the Seine in Paris, 110 m vessel at 1.7 m draft.

The control by setting propeller rate and rudder angle is shown in Figure 11 with the human controlled settings left and the track controller settings right. Now the model-free controllers are also compared. In SIM35 the propeller rate is often put to zero rps to control the speed with a higher variation of the rudder angle compared to SIM36 (smaller beam). The PMTC was restricted in changing the rudder angle in steps of 2 degrees with a maximum of 20 deg in one setting while the skipper and model-free controllers take large steps in rudder angle setting. The comparable rudder settings of the two model-free controllers are remarkable. This could be attributed to the same line of sight (LOS) method as input for both controllers and the linear interpolation scheme for the Fuzzy controller. For the propeller rate, the skippers often stopped the engine (especially in SIM35) while speed control was considered for the PMTC (with two different values during the shown track) and constant propeller rate for the Fuzzy or PID controller. Different gain settings for the PID controller have been checked and only a PD control with finally a negligible D gave the best control. Also increasing the propeller rate for the PID controller did not decrease the heading error.

The PMTC0, FUZZY0 and PID0 simulated paths are shown for the loading condition of 1.7 m in Figure 12 and for the maximum draft of 2.8 m in Figure 13. Thanks to the higher mass at the larger draft, the effect of wind and current on the ship behaviour and track reduces, so that the paths of model-free controlled simulations (Fuzzy and PID) are closer to the predefined track. But for both drafts and the model-free controlled simulations, the passage of a narrow bridge's arch followed by a small heading change, leads to a quick change of the rudder angle and overshoots in swept paths with touching of the bridge arch with the ship contour (downstream 169.9 km and 170.3 km).

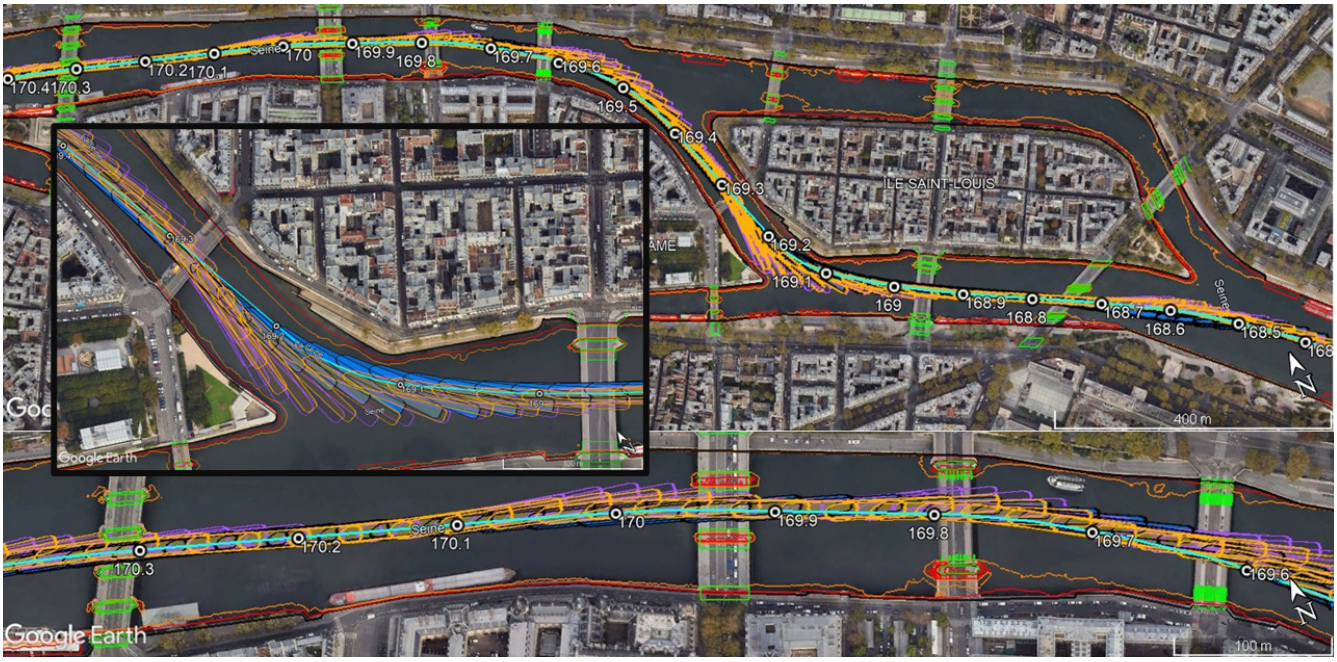


Figure 12 **Overview and detailed extractions of the PMTC0 (blue with black contour), FUZZY0 (orange) and PID0 (purple) simulated tracks of the 110 m vessel at 1.7 m draft.**

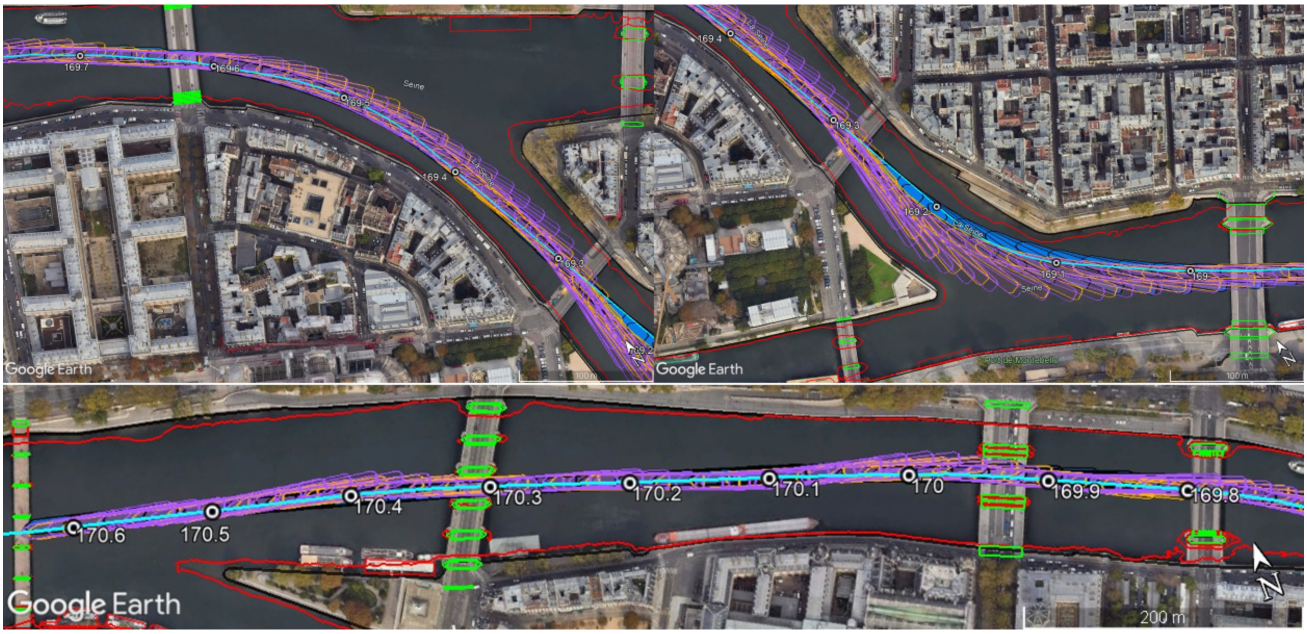


Figure 13 **Detailed extractions of the PMTC0 (blue with black contour), FUZZY0 (orange) and PID0 (purple) controlled tracks of the 110 m vessel at 2.8 m draft.**

The settings of the PMTC required weights for the cost function in equation (1) of 5, 5 and 1 (fore, mid and aft) so that the fore body of the ship should be close to the reference path and a lookahead time of 50 seconds or approximately 125 to 150 m or thus more than one ship length, taken the ship speed into account. The settings of the controllers were not changed for the considered loading conditions (first tuning for smallest draft and reuse for highest draft).

To further investigate the human or PMTC control for the specific environmental conditions at 280 cm water level, four simulations were conducted (Figure 14: SIM36, PMTC2 and PMTC4 are shown):

1. PMTC1: 1.7 m draft, same settings as previous PMTC simulations, except increased desired speed of 4 m/s and rps
2. PMTC2: 2.8 m draft, same settings as Sim1
3. PMTC3: 1.7 m draft, settings as Sim1, changed path between 170.3 and 170.6 km to correspond to human selected path

4. PMTC4: 1.7 m draft, settings as Sim3, decreased look-ahead distance (± 50% of Sim1) for better path following

Drifting is larger for the PMTC controlled vessel at 1.7 m draft compared to the human at the same draft or PMTC controlled vessel at 2.8 m draft. Loading condition has a clear influence and the use of more frequently changing rudder angles with higher values for the French skipper steered simulation gives closer tracks to the reference path.

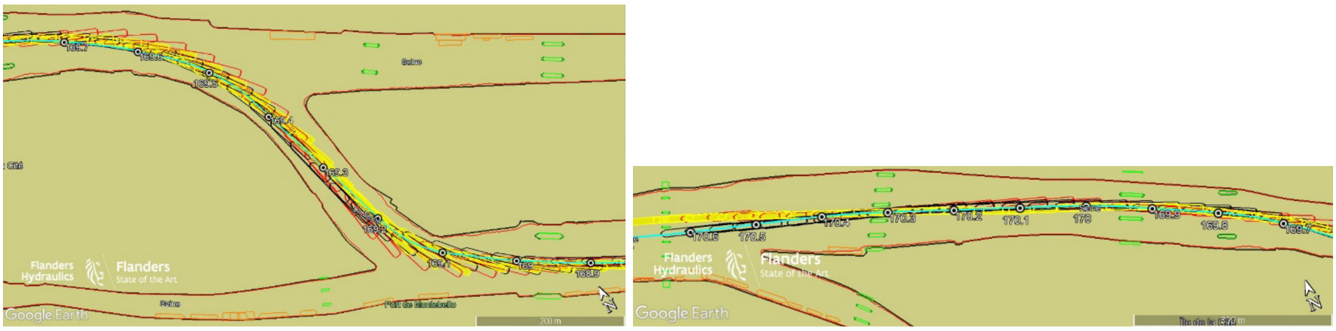


Figure 14 Zigzag manoeuvre and passage of bridges for human controlled simulation SIM36 (yellow) and PMTC controlled simulations PMTC2 (black) and PMTC4 (red) for 280 cm water level.

3.1 (b) Quantitative comparison

A quantitative comparison is made based on different control performance indexes defined by Changyuan Chen et al., (2020) and repeated in He et al. (2023). The cross track error e is the distance from point C to the reference line (W_{k-1},W_k) in Figure 15 and the heading error e_ψ is the difference between the heading of the ship (line CB) to the heading of the reference line (AB). The look-ahead distance ξ for the LOS for PID or Fuzzy controller is given as a percentage of the length between perpendiculars (0.5 to 2 L_{PP}).

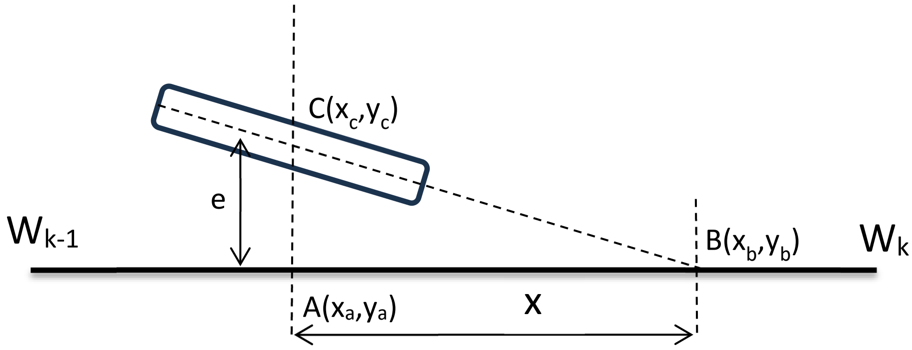


Figure 15 Cross track error e and look-ahead distance ξ for the ship with origin C in relation to the line with waypoints W_{k-1} and W_k

The performance indexes are, with N_0 and N_1 the starting and end time steps for evaluation:

1) Mean track error integral, mTEI (path following accuracy)

$$mTEI = \frac{1}{N_1 - N_0 + 1} \sum_{k=N_0}^{N_1} |e(k)| \quad (3)$$

2) Maximum track error, MTE

$$MTE = \max\{|e(N_0)|, |e(N_0 + 1)|, \dots, |e(N_1)|\} \quad (4)$$

3) Mean rudder integral, mRI (aggressiveness of rudder control)

$$mRI = \frac{1}{N_1 - N_0 + 1} \sum_{k=N_0}^{N_1} |\delta(k)| \quad (5)$$

4) Mean rudder total variation, mRTV (energy consumption on rudder)

$$mRTV = \frac{1}{N_1 - N_0} \sum_{k=N_0+1}^{N_1} |\delta(k) - \delta(k-1)| \tag{6}$$

5) Mean heading error integral, mHEI (heading control accuracy)

$$mHEI = \frac{1}{N_1 - N_0 + 1} \sum_{k=N_0}^{N_1} |e_\psi(k)| \tag{7}$$

The performance indexes for the different controller types and the human controlled simulations for the 110 m vessel at both drafts are shown in Table 2. The lowest value for each index is shown in bold. The parameters, draft and water level/current, are retaken from Table 1 to clearly show the influence of the loading condition and the discharge on the indexes. The Fuzzy and PID controllers give the largest values for the track and heading errors and for the mean rudder integral comparable values as the human controlled simulations. They do not succeed in coming close to the predefined track and the conclusion could be that model-free controllers should accept more variability in combined engine and rudder settings as is clearly seen for human controlled SIM35 and SIM36 in Figure 11.
Comparing the values for 1.7 m draft the skipper can maintain a closer track to the predefined but with much more rudder use and variability. With the PMTC controlled PMTC2 at 2.8 m draft and PMTC4 at 1.7 m, track errors are 19 to 70% higher, with the maximum track error up to 58 and 92% higher than SIM36. The heading error is lower for PMTC2 (-8%) and 40% higher for PMTC4 compared to SIM36. The mean rudder integral is approximately half of the human controlled value for all PMTC controlled simulations and by decreasing the look-ahead distance in PMTC4 the mean rudder total variation increases a bit, but far from the value skippers induce. This is clearly due to the obligation of only 2 degrees steps of rudder angle difference in consecutive decisions which will have an effect also on the track and heading errors.

Table 2 The performance indexes for the different controller types (PMTC, FUZZY and PID) compared to human controlled simulations for the 110 m.

Control/Simulation	Draft	Water level/current	mTEI	MTE	mRI	mRTV	mHEI
Name	[m]	[cm]	[m]	[m]	[deg]	[deg]	[deg]
SIM35, human	1.7	280/280	2.83	9.04	16.19	3.72	4.79
SIM36, human	1.7	280/280	2.68	**7.02**	19.78	5.82	4.15
PMTC0	1.7	120/140	**2.45**	9.20	**9.51**	0.30	3.98
FUZZY0	1.7	120/140	4.60	18.43	15.81	2.11	5.03
PID0	1.7	120/140	5.65	20.64	18.39	1.59	6.36
PMTC1	1.7	280/280	5.19	14.50	11.44	0.34	6.51
PMTC2	2.8	280/280	3.19	11.11	10.52	**0.28**	**3.82**
PMTC3	1.7	280/280	5.05	14.50	11.89	0.36	6.53
PMTC4	1.7	280/280	4.58	13.53	11.57	0.44	5.85

3.2 SHIPS ON THE WESTERN SCHELDT

The Western Scheldt, a complex estuarine environment, presents significant challenges for autonomous ship navigation due to its varying depth, strong currents, dense traffic and complex waterway geometry. This section describes the approach to develop and validate an autonomous navigation system using reinforcement learning for this river environment. While this work serves as an initial proof of principle, subsequent research will explore these concepts in greater depth.

3.2 (a) Multi-paradigm simulation methodology

The research develops an innovative methodology for training reinforcement learning (RL) agents for autonomous navigation in shallow and confined waterways using multi-paradigm simulation. Traditional approaches often rely on computationally intensive, high-fidelity simulators, which can make the training process prohibitively expensive and time-consuming. The proposed methodology addresses this challenge by leveraging a hierarchical approach to simulation fidelity. The core of the approach is a modular framework that enables the seamless integration of different simulators and AI solutions. This framework allows training to begin with computationally efficient, low-fidelity simulations and progressively incorporate higher-fidelity models for specific aspects of the system dynamics. By incrementally introducing new paradigms and more detailed physics models, the trade-off between training efficiency and model accuracy can be optimized.

In this initial study, the feasibility of the approach is demonstrated through a two-stage process, starting with a computationally efficient 2D environment before moving to the Flanders Hydraulics simulator. Future work will focus on extending the training methodology to incorporate additional paradigms and simulators, further validating the effectiveness of the modular framework for developing robust autonomous navigation systems.

3.2 (b) Simulation definition

A custom 2D continuous environment was developed that roughly represents the Western Scheldt's navigational challenges. The simulation environment implements a simplified linear ship dynamics model based on three degrees of freedom (surge, sway and yaw). At the core of the simulation is a comprehensive state space that captures relevant aspects of the ship's motion and its relationship to the environment.
The state vector s_t at time t defined in Eq. (8), comprises thirteen variables that describe the ship's condition and its navigational context.

$$s_t = [x,\, y,\, \psi,\, u,\, v,\, r,\, d_c,\, d_{c+1},\, d_{c+2},\, e_c,\, e_h, \delta,\, T] \tag{8}$$

In the state vector defined in Eq. (8), the ship's position is defined by coordinates (x, y) and ψ represents the heading. The vessel's motion is characterized by three velocity components: surge velocity u (longitudinal), sway velocity v (lateral), and yaw rate r (rotational velocity). To enable effective navigation, the state space incorporates several navigational parameters: the distances to three sequential checkpoints (d_c for current, d_{c+1} and d_{c+2} for the next two), along with two error measurements—cross-track error e_c (lateral deviation from the planned path) and heading error e_h (difference between actual and desired heading). The state representation is completed by the actual control inputs: rudder angle δ and propeller thrust T.

This model is described by a set of differential equations that couple these motions while accounting for hydrodynamic effects and control inputs. The ship's equations of motion in the 3-DOF model are expressed as a set of coupled differential equations defined in Eq. (9), (10) and (11). Inertial and centripetal forces and moment are neglected which gives a significantly simplified but first model for training.

$$\frac{du}{dt} = k_t \cdot T + X_u \cdot u \tag{9}$$

$$\frac{dv}{dt} = k_v \cdot \sin(\delta) \;+\; Y_v \cdot v \tag{10}$$

$$\frac{dr}{dt} = k_r \cdot \delta + \; N_r \cdot \frac{v}{L} \tag{11}$$

Eq. (9) models the surge dynamics, where thrust T is scaled by the thrust coefficient k_t and dampened by the hydrodynamic coefficient X_u. Eq. (10) describes sway motion, where the rudder angle δ influences lateral movement through the sway coefficient k_v, with Y_v providing hydrodynamic damping. Eq. (11) governs the yaw motion, coupling the rudder angle effect k_r with the sway-induced moment and damping N_r, scaled by the ship's length L.

The action space for the autonomous navigation system consists of two continuous control variables: rudder angle and thrust. Both actions are mapped in a range [-1, 1] and then transformed to physical parameters. This mapping ensures that the reinforcement learning agent calls realistic bounds while maintaining a normalized action space for training stability.

The reward function synthesizes multiple aspects of navigation performance into a single scalar signal. Distance-based progress is rewarded through a hyperbolic tangent function of position changes, while heading alignment is encouraged through a cosine relationship with the desired course. Cross-track error is penalized using a scaled hyperbolic tangent function, providing strong feedback for path-following behaviour while maintaining smooth gradients for learning. Additional rewards are provided for checkpoint progression, with the magnitude scaled by the relative progress through the course. Terminal rewards and penalties provide clear feedback for successful navigation or various failure conditions.

3.2 (c) Proximal policy optimization (PPO) implementation

The autonomous navigation system employs Proximal Policy Optimization with an actor-critic architecture designed specifically for the complexities of ship navigation. The neural network architecture begins with a shared processing backbone that feeds the 13-dimensional state input through two fully connected layers of 256 and 128 units respectively, each followed by ReLU activation functions. This shared representation captures the fundamental features of the navigation state before branching into specialized actor and critic networks.
The actor network outputs both the mean and standard deviation of a Gaussian policy distribution, with the mean processed through a tanh activation to bound the control outputs appropriately. This stochastic policy enables exploration during training while maintaining smooth control outputs suitable for ship navigation. The critic network provides state value estimates that enable advantage estimation for policy updates.

3.2 (d) Training and validation

As proof of principle, the agent was trained in the low-fidelity computationally efficient 2D environment and then tested in the Flanders Hydraulics simulator. The training process spanned 1300 iterations, with five complete navigation episodes each. Each episode initializes the ship with slight position perturbations around the starting coordinates, introducing variability that promotes robust policy learning.

During each iteration, the collected experiences are used for ten epochs of policy updates. The advantage values are normalized within each batch to improve training stability, and an entropy bonus with coefficient 0.01 encourages exploration of the action space. The PPO algorithm optimizes the policy using a clipped surrogate objective function that balances learning stability with policy improvement. The clipping parameter is set to 0.2, preventing excessive policy updates that could destabilize learning. The advantage estimates utilize Generalized Advantage Estimation (GAE) with a discount factor of 0.99 and a GAE parameter of 0.95, providing a good balance between bias and variance in the policy gradient estimates. The learning process is monitored using metrics including the average episode reward and policy loss. This last is computed using a composite loss function that combines policy improvement with value function learning and entropy regularization. The mTEI, MTE and mHEI metrics defined in equations (3), (4) and (5) respectively, were used to measure the accuracy of the model.

Following initial training in the computationally efficient 2D simulation environment, the agent's performance was validated in the Flanders Hydraulics simulator. This sophisticated simulator provides substantially enhanced physical modeling, including full 6DOF ship dynamics, detailed hydrodynamic current models, high-resolution bathymetry, and realistic environmental conditions.

Table 3 The performance indexes for the trained agent tested in both simulators (mTEI, MTE and mHEI).

	mTEI	MTE	mHEI
Environment	[m]	[m]	[deg]
2D simulator	0.57	3.95	3.44
FH simulator – no wind and no current	21.38	54.24	6.88
FH simulator – wind and no current	24.91	60.66	8.59
FH simulator – wind and current	46.60	164.28	10.31

The initial testing results presented in Table 3 and visualized in Figure 16 demonstrate varying levels of performance across different simulation environments. While the agent achieved promising accuracy in the 2D environment with relatively low error metrics (mTEI of 0.57 m, MTE of 3.95 m, and mHEI of 3.44 degrees) due to the low fidelity of this environment, performance degraded when tested in the more complex Flanders Hydraulics simulator. The introduction of additional environmental factors led to progressively larger deviations, with the most challenging scenario (including both wind and current) resulting in a mTEI of 46.60 m, MTE of 164.28 m, and mHEI of 10.31 degrees. It is important to note that these results represent preliminary findings from an initial proof-of-principle implementation. Future research will focus on optimizing the training process through enhanced simulation paradigms and more sophisticated training methodologies, which is expected to significantly reduce these error margins and improve overall navigation performance.

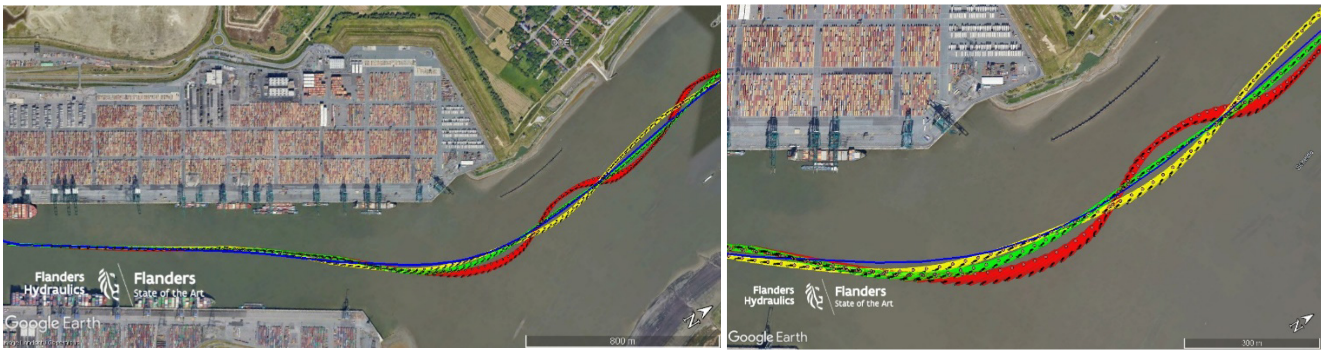


Figure 16 Test of a trained agent (using low fidelity simulator) in the Flanders Hydraulics research simulator using three different configurations (reference track in blue): no wind and no current (green path), wind and no current (yellow path), wind and current (red path).

4 CONCLUSIONS

If autonomous navigation in dense harbours and waterways will be made possible, knowledge on different domains will have to be incorporated. In this paper researchers with different backgrounds are joining together through the DDSHIP project for Data-driven Smart Shipping. In the project situational awareness of the surrounding waterborne world for the autonomous ship is combined with model predictive control with models describing the environmental conditions and ship behaviour in very diverse situations and AI trained agents through reinforcement learning.

The paper gives a description of model-based and model-free track controllers that have been used for systematic research on the accessibility of ships in shallow and confined waterways and port areas for sea-going and inland ships. The pre-science model-based track controller (PMTC) applies advanced mathematical models for the prediction of shallow water manoeuvring, ship-bank and ship-ship interaction and environmental models (current, wind) in the prediction phase of the controller. In this phase engine/propeller and rudder settings are providing track predictions which are compared with the predefined track so that the best control setting can be chosen. Many parameters define these decisions and even more are to be included to mimic or replace the human controlled handling. Model-free track controllers, as Fuzzy and PID, do not know the physical constraints for a ship in a dense traffic lane but reduce the deviation and heading errors for the predefined path.

Because in manoeuvring the number of determining parameters are large, the aim is to introduce model predictive reinforcement learning controllers which are enriched by mathematical models on the physics. The question arises in which specific part, path planning or path following, the most domain knowledge should be included or if both, setting the path and following with a controller, are intertwined as the path should be realistic in the given situation for the ship and loading condition and the ship controls should suffice to avoid collisions.

In the examples the PMTC, Fuzzy and PID controllers are compared to each other for the passage of the river Seine in Paris with a zigzag manoeuvre and passages of bridges in a confined river under wind and current. The predefined track which is followed by the controllers, is based on human controlled tracks which were derived from simulations but in real life could be derived from AIS tracks. Nevertheless, the variety in tracks is large so that situational awareness and path planning algorithms should define regularly updated paths for collision avoidance in economical and ecological ways. The performance of the PMTC, due to its large domain knowledge, is coming closest to the human controlled simulations on the same simulator platform of Flanders Hydraulics. The disadvantage of the PMTC is that such high-fidelity models require an enormous amount of physics based data and modelling. Therefore with the proof of principle for an inland ship on the Western Scheldt the University of Antwerp illustrates the multi-paradigm simulation methodology for training of model predictive reinforcement learning controllers. The focus is on path-following but could also be used for path planning. The simplified ship behaviour model on which the control agent is trained, does not suffice if the performance is tested on the Flanders Hydraulics simulator but at least the start is given for a further exploration of adding more precise surrogate models to improve the setup. The DDSHIP project will run until end 2026.

5 ACKNOWLEDGEMENTS

The authors want to acknowledge the subsidy organization VLAIO from the Flemish Government for the DDSHIP project. De Blauwe Cluster is the agency that led the proposals request and that supports the cluster strategic research for the partners: Flanders Hydraulics (coordinator), University of Antwerp and Ghent University. Acknowledgements are also for the valuable insights the project “Etude des conditions de navigation dans la traversée de Paris” for the French waterway authority Voies Navigables de France gave on traffic handling on the river Seine in Paris.

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