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PIONEERS

Portable Innovation Open Network for
Efficiency and Emissions Reduction Solutions

D7.8 – DEMONSTRATOR FOR REAL-TIME SUPPORT TRAFFIC CONTROL

PAWEŁ KOŁODZIEJCZYK, CORNELIS VERSTEEGT

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PIONEERS

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Author(s) & contributors	
Main Contributor(s)	Paweł Kołodziejczyk & Cornelis Versteegt (Macomi)
Contributor(s) (alphabetical order)	Menno Oudshoorn

Quality control		
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Acronyms and Abbreviations	
Acronym/Abbreviation	**Meaning**
AI	Artificial Intelligence
AIS	Automatic Identification System
ADE	Average Displacement Error
APICA	Advanced Port Intelligence & Coordination Assistant
CINEA	European Climate, Infrastructure and Environment Executive Agency
DSS	Decision Support System
DST	Decision Support Tool
EC	European Commission
ETD	Estimated Time of Departure
FDE	Final Displacement Error
GRU	Gated Recurrent Units
JIT	Just in time
LNG	Liquefied Natural Gas
MLP	Multi-Layer Perceptrons
MMSI	Maritime Mobile Service Identity
OR	Operations Research
PoAB	Port of Antwerp-Bruges
PPMR	Point Position Miss Rate
PSAVR	Point Sailable Area Violation Rate
RNN	Recurrent neural network
RoRo	Roll-on/Roll-off
TPMR	Trajectory Position Miss Rate
TSAVR	Trajectory Sailable Area Violation Rate
WP7	Work Package 7

Disclaimer

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Executive Summary

The EU-funded PIONEERS project aims to develop sustainable, smart, green and resilient ports across Europe, with the Port of Antwerp-Bruges serving as a lighthouse port. As part of this broader transformation initiative, this deliverable (D7.8) addresses a critical component of port modernization: real-time vessel traffic optimization. We present a breakthrough in traffic management through the development of an AI-powered Decision Support Tool that can predict vessel movements 30 minutes in advance with high accuracy, directly contributing to the project's sustainability, efficiency, and emission reduction goals aligned with the European Green Deal.

European ports handle over 3.5 billion tonnes of cargo annually, but inefficient vessel traffic management leads to unnecessary waiting times, increased fuel consumption, and higher emissions. Traditional traffic control systems are reactive rather than predictive, missing opportunities for optimization that could significantly reduce the environmental impact of maritime operations.

We developed an artificial intelligence system that analyzes real-time vessel data to predict future movements, enabling port operators to make proactive decisions that reduce congestion and emissions. The system was successfully tested at the Port of Antwerp-Bruges, one of Europe's largest ports, demonstrating its practical applicability for widespread deployment across the EU port network.

Key Achievements:

- Created AI models that predict vessel trajectories 30 minutes ahead with sufficient accuracy for operational decision-making
- Successfully integrated with existing port infrastructure through the APICA digital twin platform
- Demonstrated measurable improvements in traffic flow optimization during live testing
- Developed a scalable cloud-based solution ready for deployment across multiple European ports

This innovation directly supports EU objectives for sustainable transport, digital transformation, and emission reduction in the maritime sector. The technology provides a practical pathway for ports to meet increasingly stringent environmental regulations while maintaining operational efficiency and competitiveness.

The successful demonstration at Port of Antwerp-Bruges proves that AI-driven traffic optimization can be implemented in complex, high-traffic port environments. The modular design allows adaptation to different port configurations across Europe, potentially benefiting the entire EU maritime network.

This deliverable represents a significant step toward the digitalization and decarbonization of European ports as envisioned by the broader PIONEERS initiative, providing policy makers with a proven technology solution that balances environmental sustainability with economic competitiveness within the comprehensive framework of port transformation.

1 – Introduction

European maritime transport faces an urgent transformation challenge. As the backbone of EU trade—handling 90% of external trade and 40% of intra-EU trade—ports must simultaneously increase efficiency, reduce environmental impact, and adapt to growing cargo volumes. The PIONEERS project addresses this challenge by developing innovative solutions for sustainable port operations, with the Port of Antwerp-Bruges serving as lighthouse port.

This deliverable focuses on one of the most persistent problems in port operations: the reactive nature of vessel traffic management. Currently, port operators respond to traffic situations as they develop, rather than anticipating and preventing bottlenecks before they occur. This reactive approach leads to vessel queues, extended waiting times, and unnecessary fuel consumption—directly contradicting EU sustainability goals and the European Green Deal's maritime decarbonization objectives.

1.1 Policy Context and Objectives

The development of this Decision Support Tool aligns with several key EU policy priorities:

Environmental Sustainability: Reducing unnecessary vessel waiting times directly decreases fuel consumption and emissions within port areas. When vessels wait at anchorages or in front of locks, they continue burning fuel while producing no economic value. Our predictive system enables proactive traffic management that minimizes these inefficiencies, contributing to the EU's goal of reducing transport emissions by 90% by 2050.

Digital Transformation: The solution exemplifies the EU's Digital Single Market strategy by demonstrating how artificial intelligence and real-time data analytics can transform traditional industries. The system integrates multiple data sources and uses machine learning to provide actionable insights, showcasing the practical benefits of digital technologies in critical infrastructure.

Economic Competitiveness: Efficient port operations are essential for European economic competitiveness. By reducing vessel delays and optimizing traffic flows, the system helps maintain Europe's position as a global maritime hub while reducing operational costs for shipping companies and port authorities.

Resilience and Adaptability: Modern ports must handle increasing traffic volumes while adapting to climate change impacts such as extreme weather events. The AI system's ability to predict and optimize vessel movements enhances operational resilience by enabling proactive responses to changing conditions.

1.2 Technical Innovation Overview

The Decision Support Tool represents a significant advancement over existing port management systems. Traditional approaches rely on predetermined schedules and manual coordination, which cannot adapt quickly to dynamic conditions. Our AI-powered solution continuously analyzes real-time data to predict vessel behavior, enabling unprecedented levels of operational optimization.

PortGenie Integration: The system builds upon PortGenie, an advanced digital twin platform that models all aspects of port operations including vessel movements, terminal operations, infrastructure constraints, and resource allocation. This comprehensive modeling capability ensures that predictions account for the complex interdependencies that characterize modern port operations.

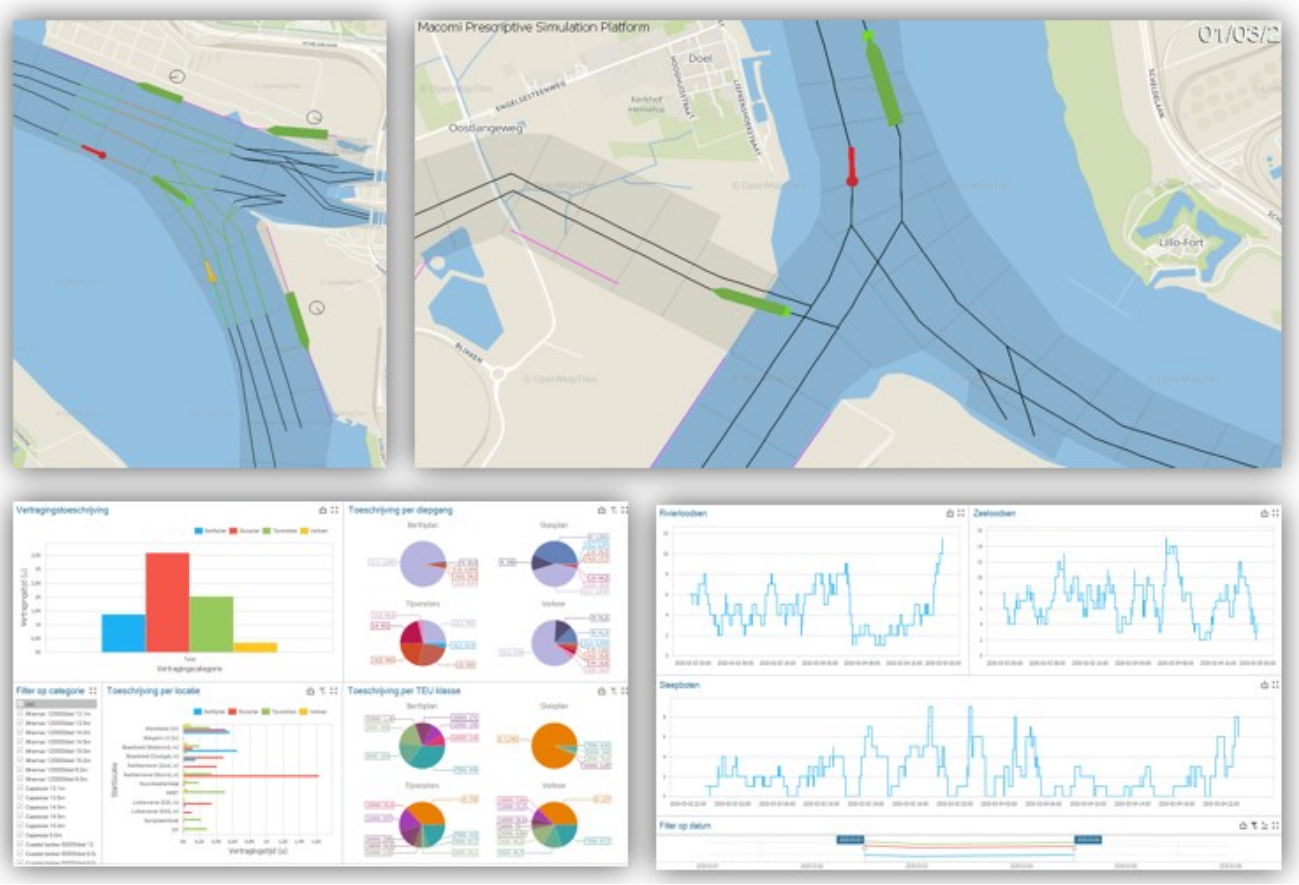

Figure 1. PortGenie impression screenshots

Real-Time Decision Support: By providing 30-minute advance predictions of vessel movements, the system gives operators sufficient time to implement traffic management interventions. This prediction horizon was specifically chosen based on expert consultation to balance prediction accuracy with operational utility—long enough to enable meaningful interventions, but short enough to maintain high accuracy.

The technology addresses a gap in current port management capabilities by moving from reactive to predictive operations, offering EU policy makers a concrete example of how artificial intelligence can deliver both environmental and economic benefits in critical infrastructure sectors.

2 – The challenge of live predictions

Vessel trajectory predictions are methods or models used to forecast the future path or movement of a ship or maritime vessel based on various inputs. These predictions are crucial for navigation safety, traffic management, collision avoidance, and maritime surveillance.

Given the goal of predicting 30 minutes ahead (that period was chosen by experts as the best trade-off between prediction accuracy and necessary time to carry out operational interventions), Macomi decided to use data-driven models, utilising AI for the predictions and training it based on historical performance. The question then is how to use the historical AIS data to train the models to predict the future.

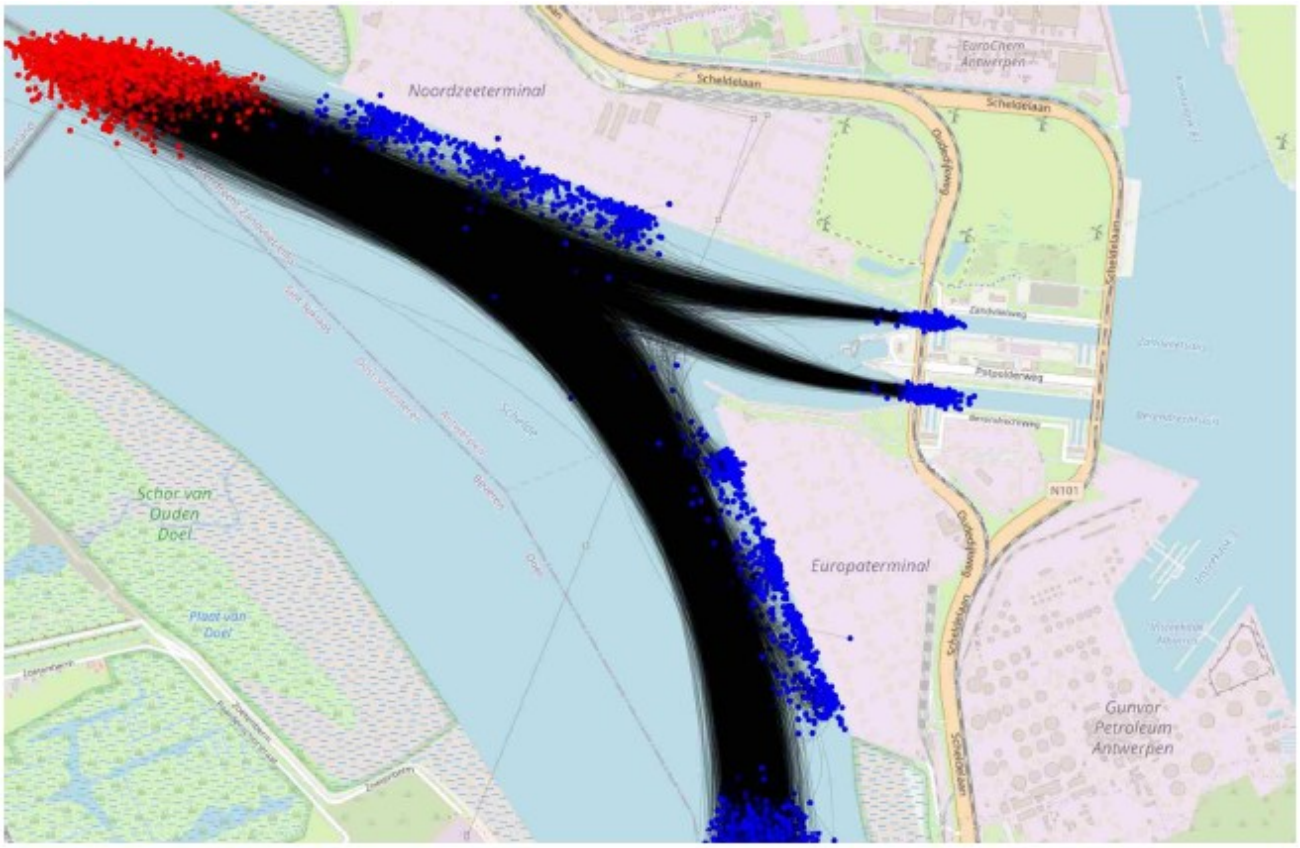

Figure 2. Superimposed over 8 thousand historical vessel trajectories

Next to predicting the sailing trajectory of vessels more difficult aspects need to be accounted for:

- Speeds and heading
- Swing characteristics (location, heading, duration, time)
- Berthing location

- Exit time and order from a lock
- Arrival/exit times of vessels

In the context of berthing, vessel swinging refers to the controlled rotation of the vessel --- often by using engines, thrusters, tugboats, or rudder --- to align the vessel's heading with a desired direction, typically to face a berth, dock, or channel. In the case of PoAB, vessels calling terminals at the Scheldt river come from the sea in the North and will eventually have to rotate to exit the same way. Rotation, or swing, can happen before or after berthing. This manoeuvre is not pre-determined and is often decided based on the traffic conditions at the time.

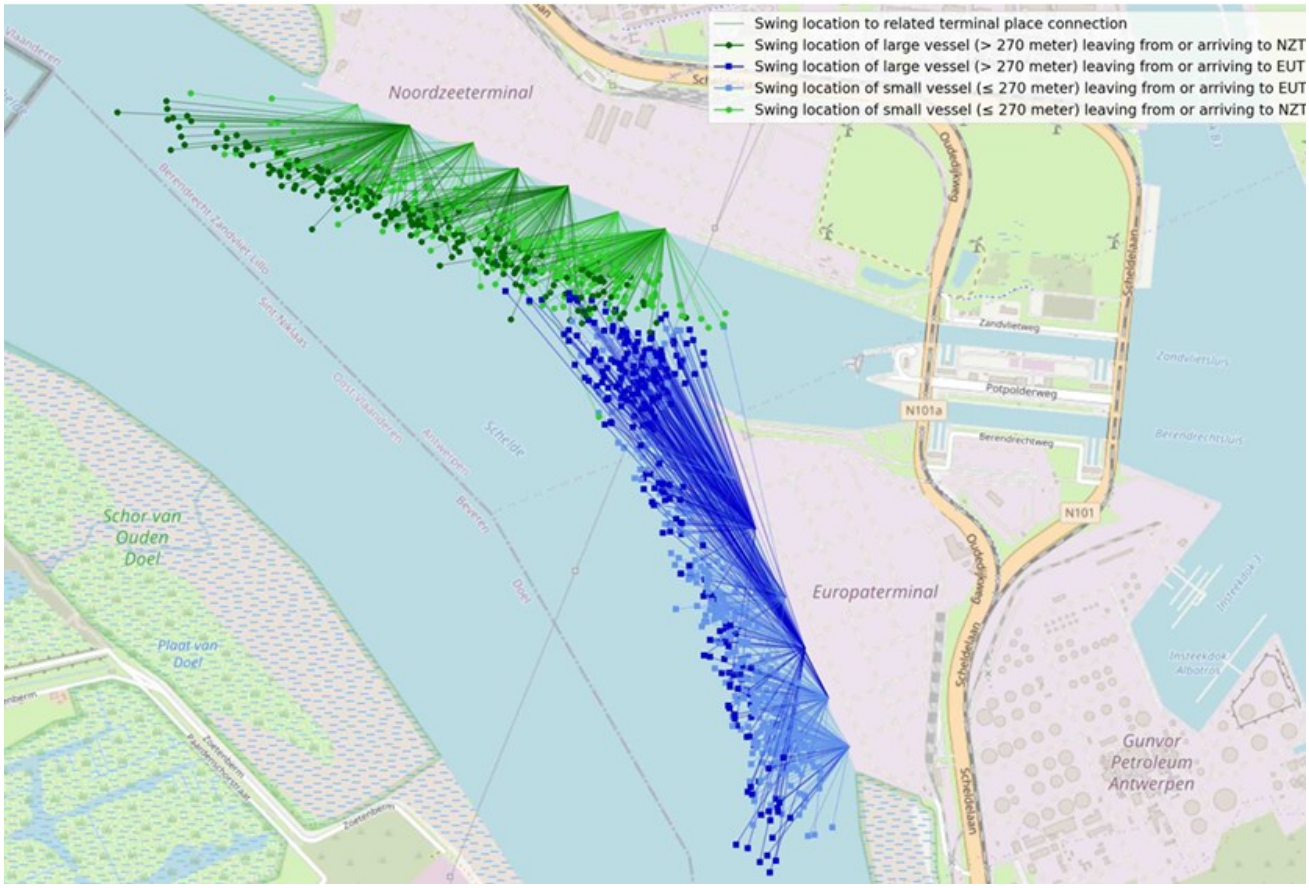

Figure 3. Illustration of historical correlation between a berthing spot and swing location.

Therefore, a prediction is made based on the historical performance. Figure 3 shows the historical correlation of berthing spot and swing centre location that illustrates the challenge faced, as next to determining when the swing will happen, it is also necessary to predict its location (start and end) as well as duration.

3 – Required data

There are two main components of the data used: AIS data and lockage characteristics. Both are obtained from PoAB's digital twin APICA and are updated every 30 seconds (with lock data updated every 5 minutes).

The following AIS data is used:

- Vessel metadata
  - MMSI
  - Type
  - Width, length, draught
- Voyage data (current and next voyage)
  - ID
  - Origin and destination
  - Berth ETD (when relevant)
- Current position of the vessel
  - Latitude / Longitude
  - Speed
  - Heading / Course over ground

When doing a prediction, we also obtain the latest lock schedule data. For each lockage we get:

- Lock and direction
- State (planned, currently executing, finished)
- (Planned) start and end time, gate closed time
- MMSI of vessels planned in the lock and the order they enter in

The lock data is necessary due to the chosen scope of the case study at PoAB on the river Scheldt next to the Berendrecht-Zandvliet lock complex as depicted in Figure 2.

4 – Solution components

The solution is divided into two parts: a pre-processing module that prepares the data, and an AI prediction module which work in sequence.

Pre-processing module handles:

- Lock planning: order and time of vessels exiting the lock
- Berth departure windows
- Sailing vessels position and heading/speed characteristics

AI Prediction module main characteristics:

- Periodical execution, loading data from pre-processing module
- Run path prediction module (single or sequential positions)
- Return predicted paths to APICA

Specifically, the preprocessing steps performed:

- Determine the current tide
- Determine whether the vessel will interact with a lock
- Interpolate the historical trajectory
    - The neural network is trained on timestamps that are exactly 30 seconds apart, so if the raw data is not, the positions are interpolated to match the expected interval
- Determine origin/destination of the vessel for the prediction module
    - We use six locations: Europa terminal, Northsea terminal, Zandvliet lock, Berendrecht lock, North (towards sea), South (towards Deurganckdok)
- Determine whether a, and what type of, prediction is needed
    - For example, vessels that are not expected to leave the berth soon don't need to be predicted
    - Vessels that are still outside the scope, but expected to enter it within the next 30 minutes, need to be predicted from the time they are expected to sail into the scope
    - Vessels that are already in the scope need to be fully predicted

The AI prediction module predicts the trajectory of a single vessel, given its historical trajectory and other metadata. The core of the module is a recurrent neural network:

- This type of network is designed to process sequential data. The positional data of vessels over time is a great example of this type of data, as there is a clear relation between the position of a vessel now, and its position 30 seconds ago
- A separate model has been trained for each combination of origin and destination. For example, North→Zandvlietsluis, or Europaterminal→North. This helps the models to focus on vessels that sail a similar route and improves prediction quality, for a small trade-off in flexibility in case of expanding the scope.
- Macomi experimented with several neural network architectures for this project

The architecture used is a combination of **G**ated **R**ecurrent **U**nits for encoding the input (historical data) and decoding the output (realized, predictions), and **M**ulti-**L**ayer **P**erceptrons to map data between dimensions as shown in Figure 4. The model predicts two values:

- The target (***t***): Where does the vessel need to go?
- The path (***ŷ***): How does it get there?

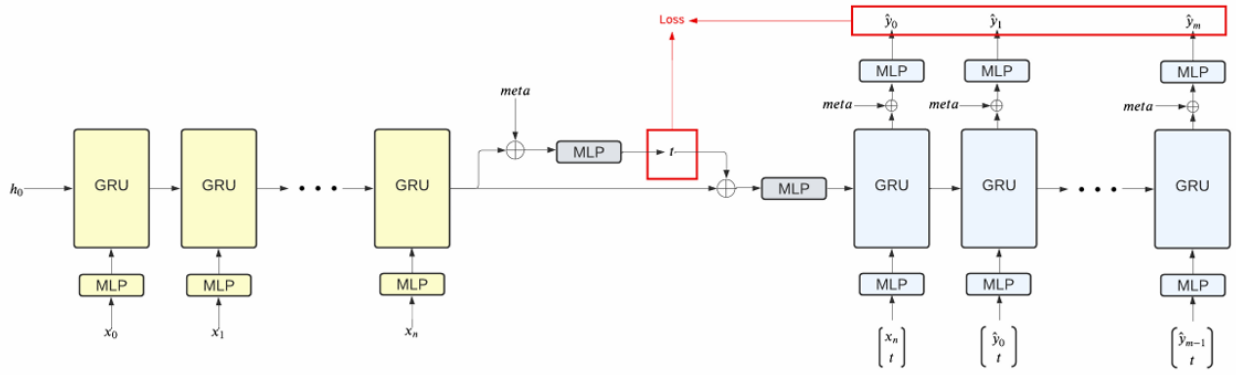

Figure 4. AI prediction architecture

The solution is hosted in the cloud and connected to PoAB's APICA as shown in Figure 5. The full solution is deployed on a Microsoft Azure cloud environment with the following characteristics:

- Azure Functions are used to periodically run the different components, as well as the AI prediction module on demand. They offer scalability and parallel processing, meaning the number of vessels to predict has little impact on the runtime
- Data is stored in a managed Azure PostgreSQL database and storage account

- Azure Monitor is used for logging and can be used for detecting issues with the application
- The use of infra-as-code makes a new deployment very easy

- Currently, the application is using real live vessel data to make and send predictions to APICA every 5 minutes

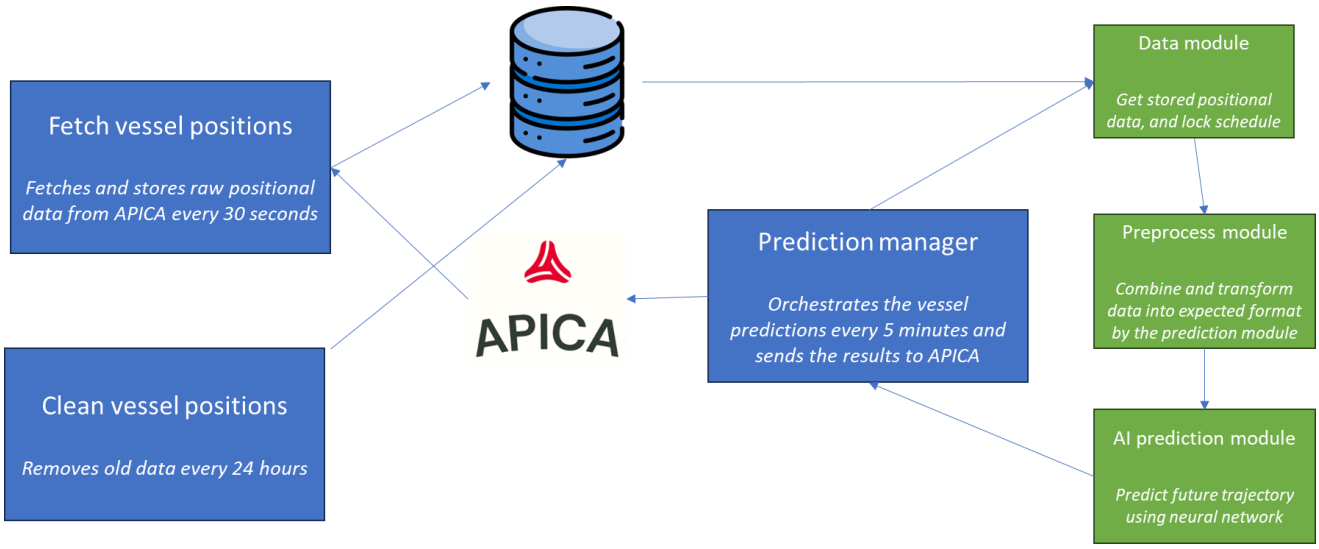

Figure 5. Cloud architecture of the solution

5 – Case study

The case study is based on the actual historical performance of the PoAB within the scope area.

The AI models are trained on the majority (about 80%) of the available historical data. The data consisted of complete two-month-long historical trajectories of all relevant vessels in the investigated area and additionally 2 years of data for container vessels. The latter was necessary due to higher variability of this type of vessel in paths, docking locations and swinging. The remainder is used for testing. The model is provided a starting trajectory of the vessel (marked in black in the following figures). Based on these few points, a projection of the future is made by the model (marked in blue) and compared with the actual trajectory (green). Then the discrepancy between the realised and predicted is the error of the solution.

Figure 6. Trajectory prediction visualisation (black: historical/input, green: realized, blue: predicted)Figure 6 shows one of the predicted trajectories for a vessel sailing from south to north. A prediction is made for about half of the trajectory of the scope in the path. The differences between the predicted and realised trajectory are low.

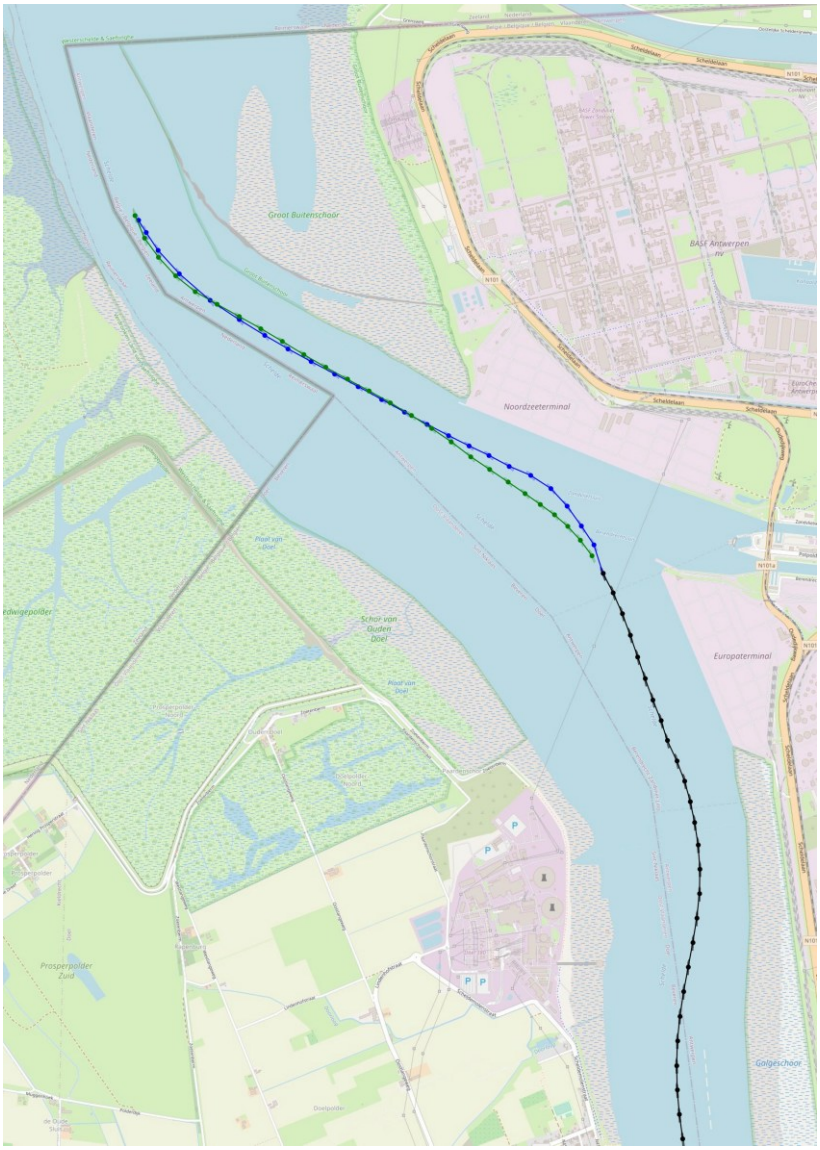

Figure 6. Trajectory prediction visualisation (black: historical/input, green: realized, blue: predicted)

Furthermore, Figure 7 shows a different trajectory where the predictor is given fewer points and at the end the vessel swings for the berth. Here too, the difference between the predicted and realised trajectory is minimal, and the swing is predicted well.

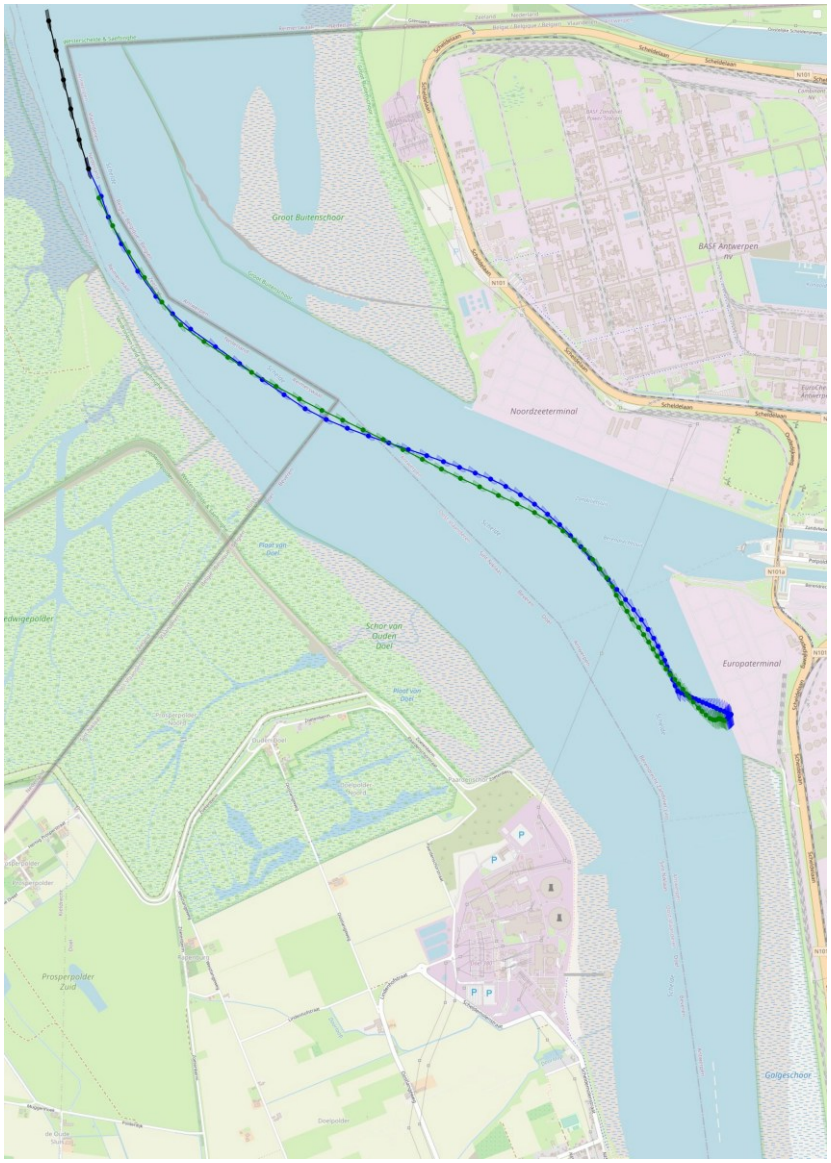

Figure 7. Trajectory with swing prediction visualisation (black: historical/input, green: realized, blue: predicted)

As the images alone cannot fully depict the accuracy of predictions, 7 varying metrics were developed. These are:

Table 1. Model accuracy metrics

Metric	Explanation
Duration error [min]	The absolute error between the predicted end time of the move and the realised one, arising from the predicted speeds
FDE [m]	Final displacement error. It is the distance between the last point of predicted trajectory and actual trajectory
ADE [m]	Average displacement error: It is the average distance (deviation) between predicted and actual trajectory
TPMR	Trajectory position miss rate. It is the ratio of unacceptable predictions (>250m) within the trajectory

PPMR	Point position miss rate. It is the ratio of unacceptable predictions (>250m) based on the predicted points
TSAVR	Trajectory sailable area violation rate. It is the proportion of predictions outside sailable area based on the total trajectory
PSAVR	Point sailable area violation rate. It is the proportion of predictions outside sailable area based on the predicted points.

Due to the performance being sensitive information for PoAB and the public nature of this report the values of the accuracy statistics of the model were redacted. These were delivered to the port authority prior to publishing this report.

6 – Conclusion

This project has successfully demonstrated that artificial intelligence can transform vessel traffic management in European ports, delivering both environmental and operational benefits that align with key EU policy objectives. The development and testing of our predictive Decision Support Tool at the Port of Antwerp-Bruges provides concrete evidence that advanced digital technologies can address pressing challenges in maritime sustainability and efficiency.

Key Achievements and Policy Implications

Environmental Impact: The system's ability to predict vessel movements 30 minutes in advance enables proactive traffic management that reduces unnecessary waiting times and associated emissions. This directly supports the European Green Deal's maritime decarbonization goals by providing ports with practical tools to minimize the environmental impact of vessel operations. The technology offers a scalable pathway for EU ports to meet increasingly stringent emission reduction targets while maintaining operational capacity.

Digital Infrastructure Development: The successful integration with existing port systems demonstrates the feasibility of implementing AI solutions in complex, mission-critical infrastructure. This achievement validates the EU's digital transformation strategy by showing how emerging technologies can enhance traditional industries without disrupting essential operations. The cloud-based architecture ensures the solution can be rapidly deployed across the European port network.

Economic Competitiveness: By optimizing vessel traffic flows, the system helps European ports maintain their competitive advantage in global maritime trade. Reduced waiting times and improved operational efficiency translate directly into cost savings for shipping companies and enhanced capacity utilization for port authorities. This economic benefit is crucial for sustaining Europe's position as a leading maritime region while transitioning to more sustainable operations.

6.1 Scalability and European-Wide Application

The modular design of our solution enables adaptation to different port configurations and operational requirements across Europe. While developed and tested at Antwerp-Bruges, the underlying AI models and system architecture can be customized for ports of varying sizes and specializations. This scalability is essential for maximizing the policy impact of the innovation, allowing both major hub ports and smaller regional facilities to benefit from advanced traffic optimization.

Implementation Readiness: The successful cloud deployment and real-time data integration demonstrate that the technology is ready for operational implementation. Port authorities can

adopt the system without major infrastructure changes, accelerating the timeline for achieving sustainability and efficiency improvements across the EU maritime network.

Standards and Interoperability: The system's compatibility with existing port management platforms and data standards facilitates integration into current operational workflows. This compatibility is crucial for policy makers seeking solutions that can be implemented efficiently without disrupting essential port operations.

6.2 Future Developments and Policy Recommendations

The project has identified clear pathways for enhancing the technology's capabilities and expanding its impact. Future research should focus on multi-vessel interaction modeling, which would further improve prediction accuracy in congested port areas. Additionally, expanding the system to cover broader port operations beyond traffic management could yield additional sustainability and efficiency benefits.

Policy Support Recommendations: To maximize the impact of this innovation, EU policy makers should consider supporting the development of common data standards for port operations and incentivizing the adoption of AI-driven optimization systems through targeted funding programs. The success of this project demonstrates that strategic investments in maritime digitalization can deliver measurable environmental and economic returns.

Strategic Importance: The technology developed under PIONEERS represents more than a technical achievement—it provides European ports with a competitive advantage in the global transition toward sustainable maritime operations. By leading in the development and deployment of AI-powered port management systems, Europe can maintain its maritime leadership while achieving critical environmental objectives.

This deliverable confirms that the integration of artificial intelligence into port operations is not only technically feasible but operationally beneficial and environmentally necessary. The successful demonstration provides policy makers with confidence that strategic investments in maritime digitalization will yield significant returns in sustainability, efficiency, and competitiveness across the European port network.

7 – References

Van Loon, J. 2023 Short-term vessel trajectory and manoeuvre prediction

Agentschap voor Maritieme Dienstverlening en Kust. Afdeling Kust. Vlaamse Hydrografie. *Getijtafel, 2022 voor Nieuwpoort, Oostende, Zeebrugge, Vlissingen, Prosperpolder, Antwerpen en Wintam*. 2021. URL: https://www.vlaanderen.be/publicaties/getijtafels- 2022- voornieuwpoort- oostende- zeebrugge- vlissingen- prosperpolder- antwerpen- en- wintam

J Kornacki and W Galor. "Analysis of ships turn manoeuvres in port water area". In: *TransNav, International Journal on Marine Navigation and Safety od Sea Transportation* 1.1 (2007).

Port Of Antwerp-Bruges. *Booklet with facts and figures of 2021 (Antwerp branch)*. 2022. URL: https://www.portofantwerpbruges.com

Port of Antwerp-Bruges. The digital twin, a third eye on the field. https://www.portofantwerpbruges.com/de-digital-twin-derde-oog-op-het-terrein

APPENDIX

Recurrent neural network

A recurrent neural network (RNN) is a type of neural network specifically designed to handle sequential data and to memorize previously seen inputs. In an RNN, the input is processed sequentially, and a hidden state is maintained throughout the process. The next hidden state is calculated as a function of both the current input and the previous hidden state. The current output is computed as a function of the current hidden state. To perform these computations, the model uses weight vectors and bias as its parameters. These parameters are optimized during the training phase.

A gated recurrent neural network is again an advancement over the vanilla RNN. GRUs can address the issue of vanishing or exploding gradients. A GRU architecture has a hidden state and internally updates this hidden state using an update gate and reset gate. The update gate determines which past information should be carried forward to the output, i.e. the next hidden state, while the reset gate decides what past information to discard. By utilizing these gates, a GRU can retain essential information from the distant past and discard irrelevant information. GRU network can handle long-term dependencies better than a vanilla RNN.

An encoder-decoder architecture with two recurrent neural networks can be utilized to predict future vessel trajectories based on historical positions. The first recurrent neural network encodes the historic trajectory into a vector embedding, while the second recurrent neural network generates a future trajectory based on this vector embedding. The vessel meta data can also be incorporated into the decoder network. This model can be trained end-to-end on the historical trajectories. In this encoder-decoder setup, the encoding network essentially summarizes the historic trajectory in a vector embedding and gives this summary to the decoder network to generate a future trajectory.