ARRIVAL-X

Final Presentation

NAVISP EL2-191

15 May 2025

www.space-ship.world

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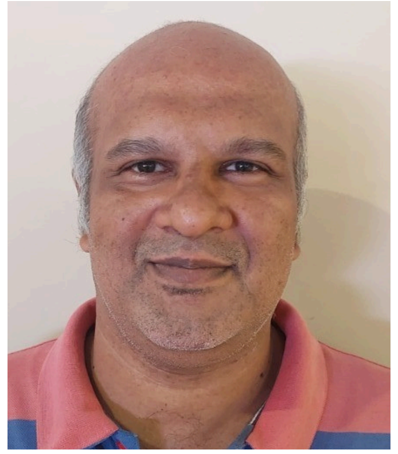

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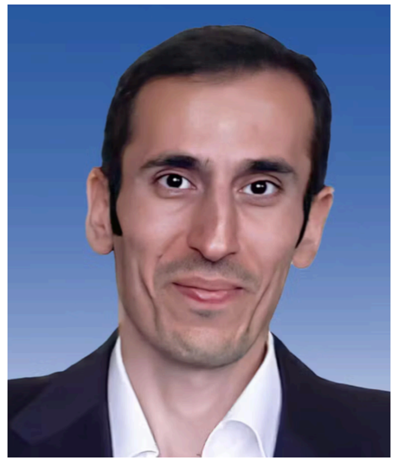

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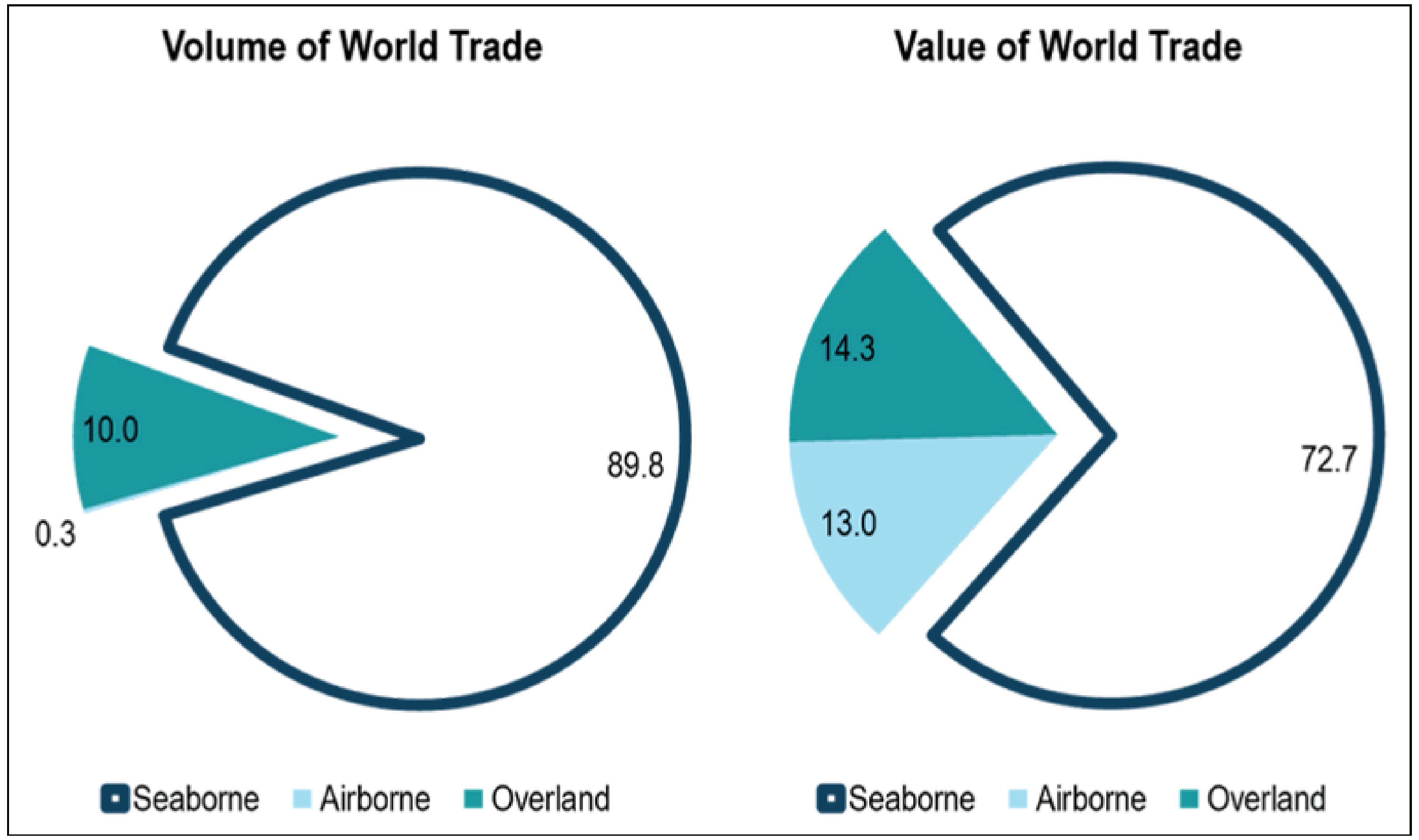
Agenda

1. Background and Motivation
2. Key Insights and Results
   - System Architecture and Components
   - Algorithm Development
   - Major Challenges
   - Pilot Test Results
3. Conclusion and Outlook

Background and Motivation

The backbone of global trade

80% of global trade is moved by ships



SPACESHIP

The current scenario

67% of all ships are late!

38% of port time is wasted waiting!

Expectations...

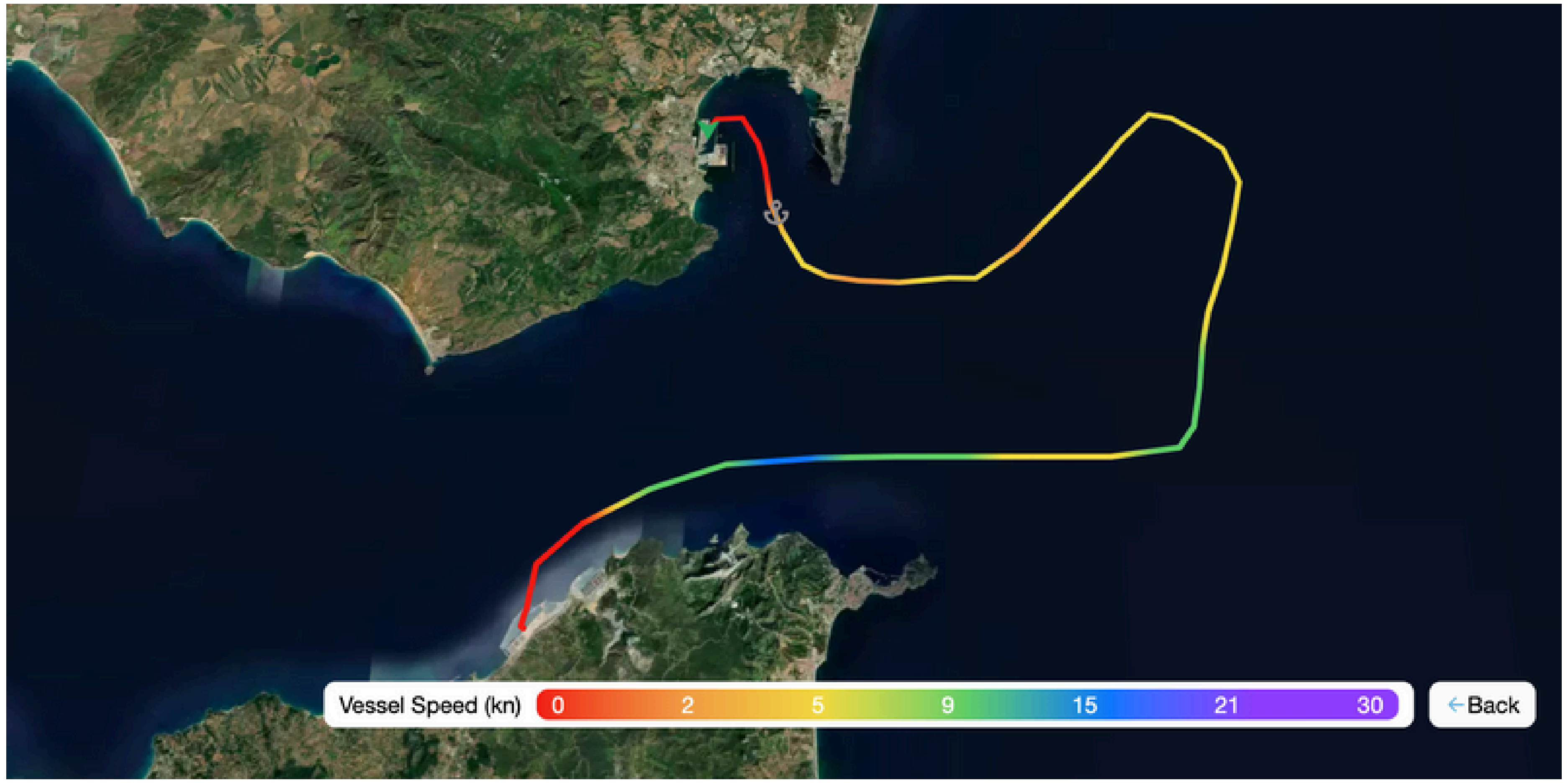
No waiting upon arrival

Linear change in speed

Timely operations and departure

Minimum emissions

No extra cost for shippers



...and in reality

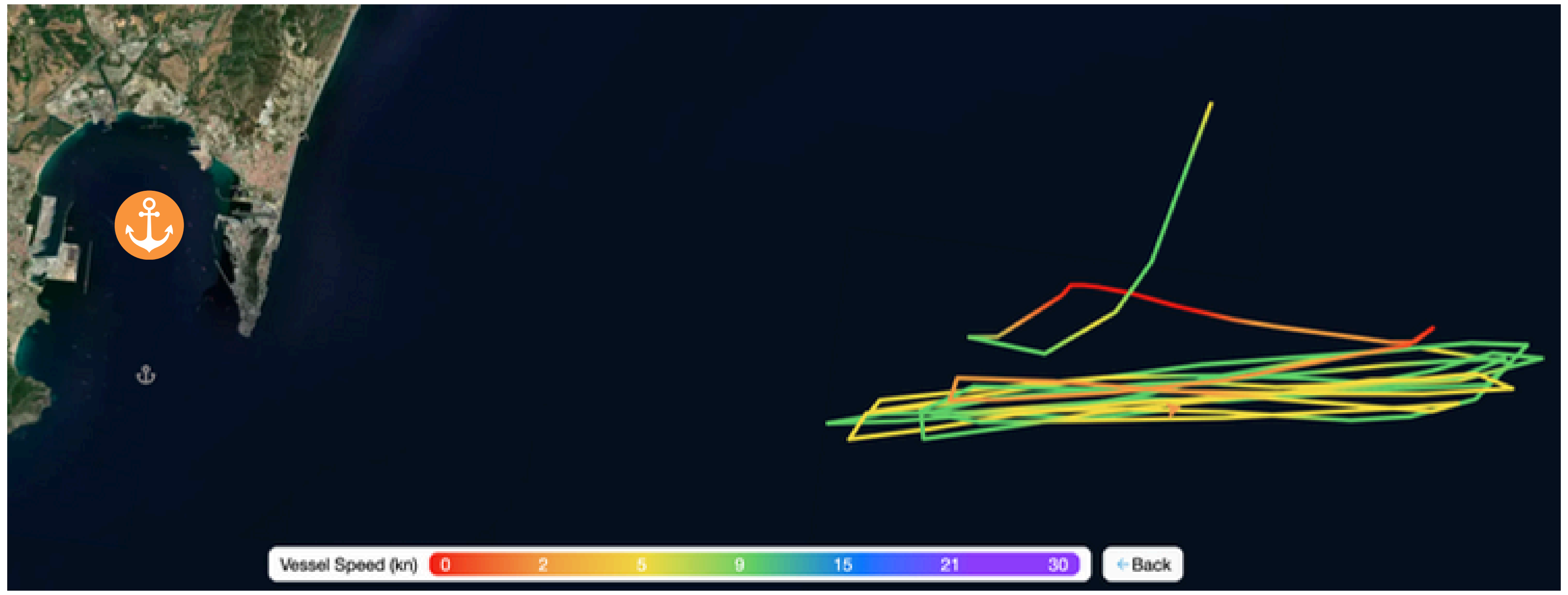
Long wait upon arrival

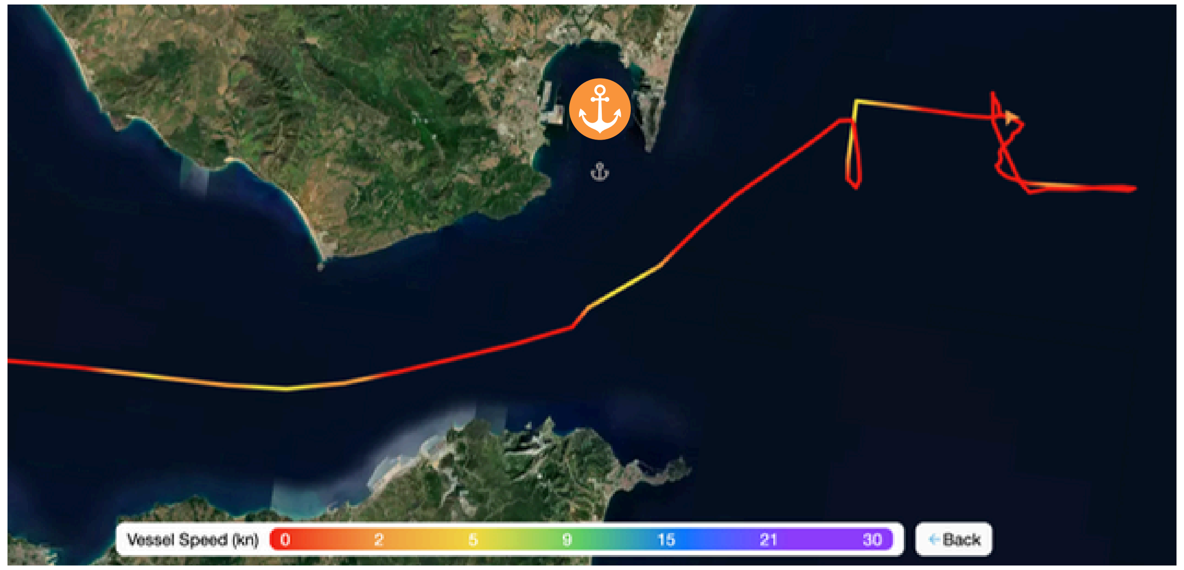
Abrupt changes in speed

Increased cost for shippers

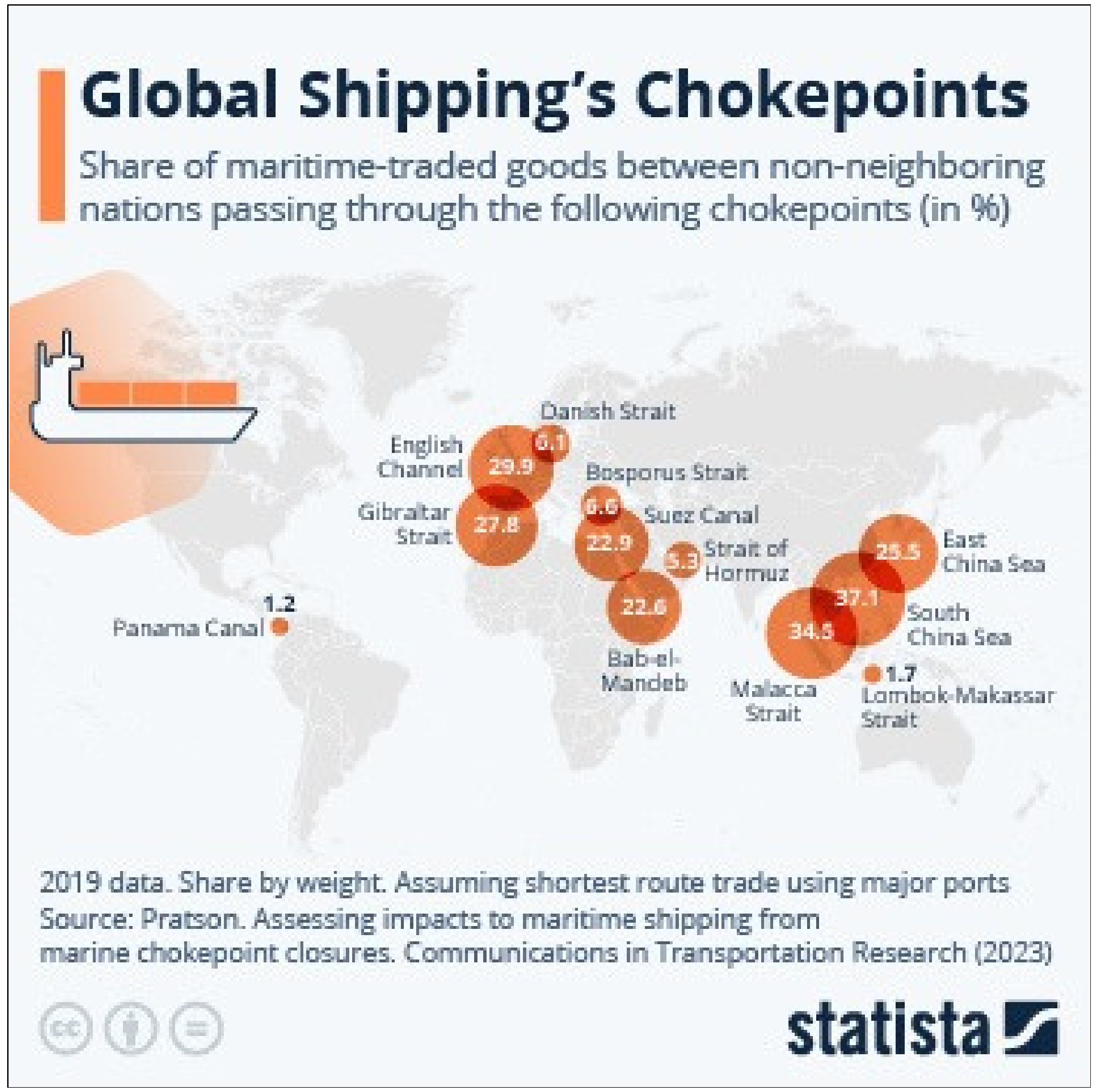
Uncertainty about operations & departure

Unnecessary fuel wastage





Economical impact



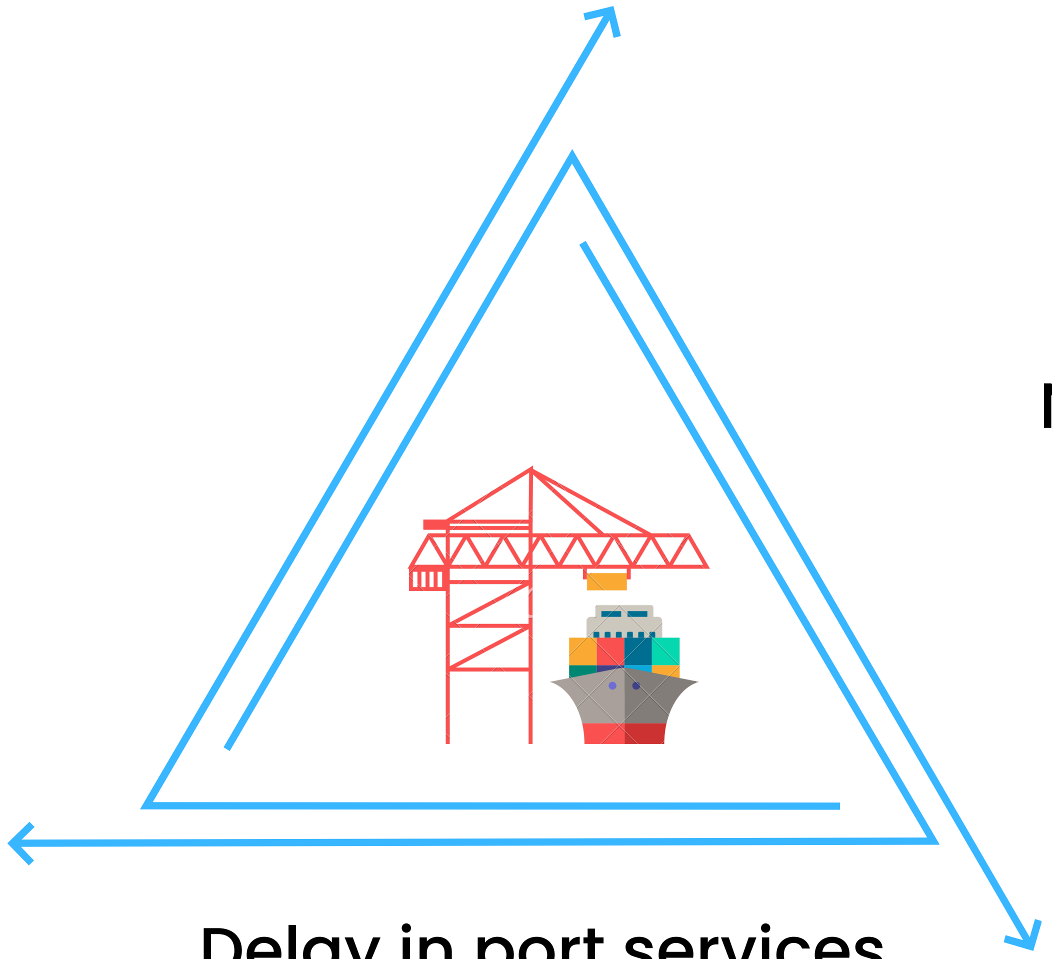
$5 billion+

Financial loss for the shippers globally due to severe vessel delays and port congestion

Source: Port Technology Report

Contributing factors

Inaccurate/Missing
ETAs

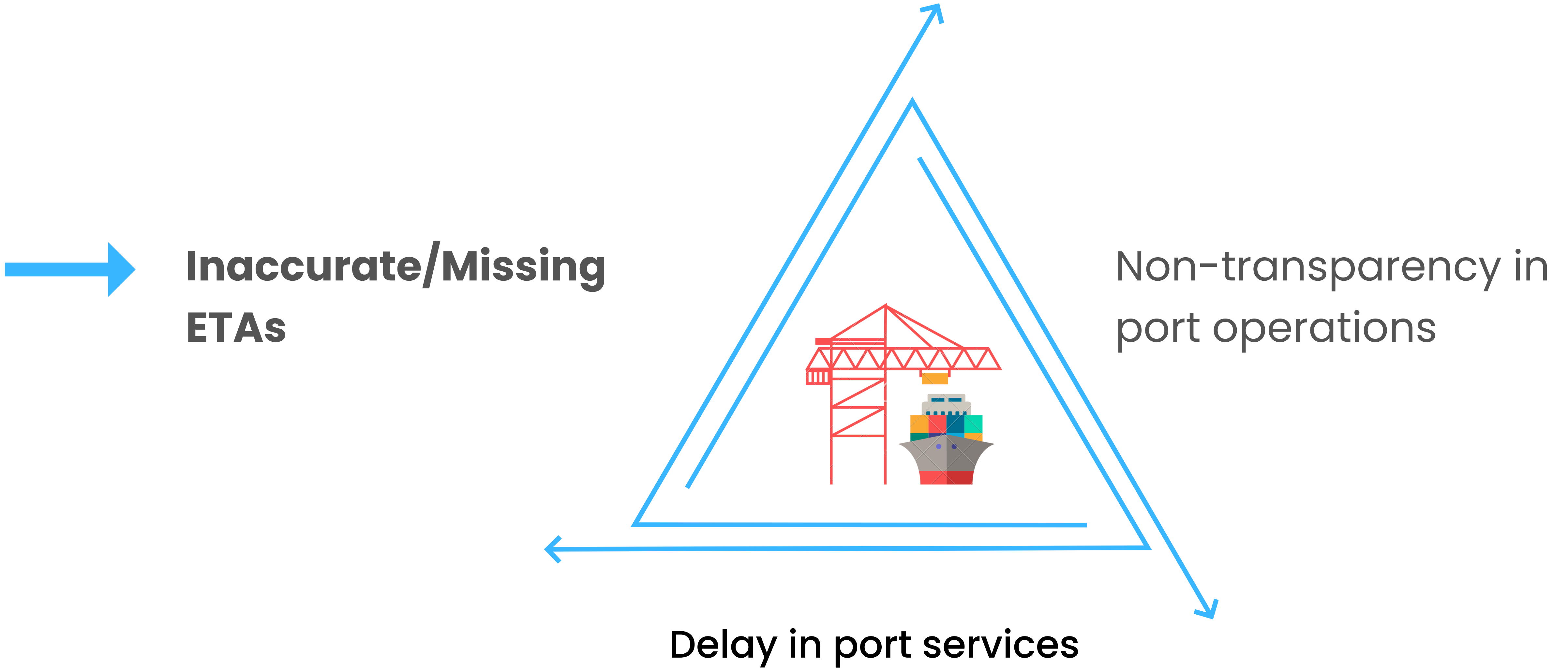


Non-transparency
is port operations

Delay in port services

Obtaining consistent and reliable data on estimated time of arrivals (ETAs) poses a well-known challenge for the Ports and Terminal Operators.

Our Vision

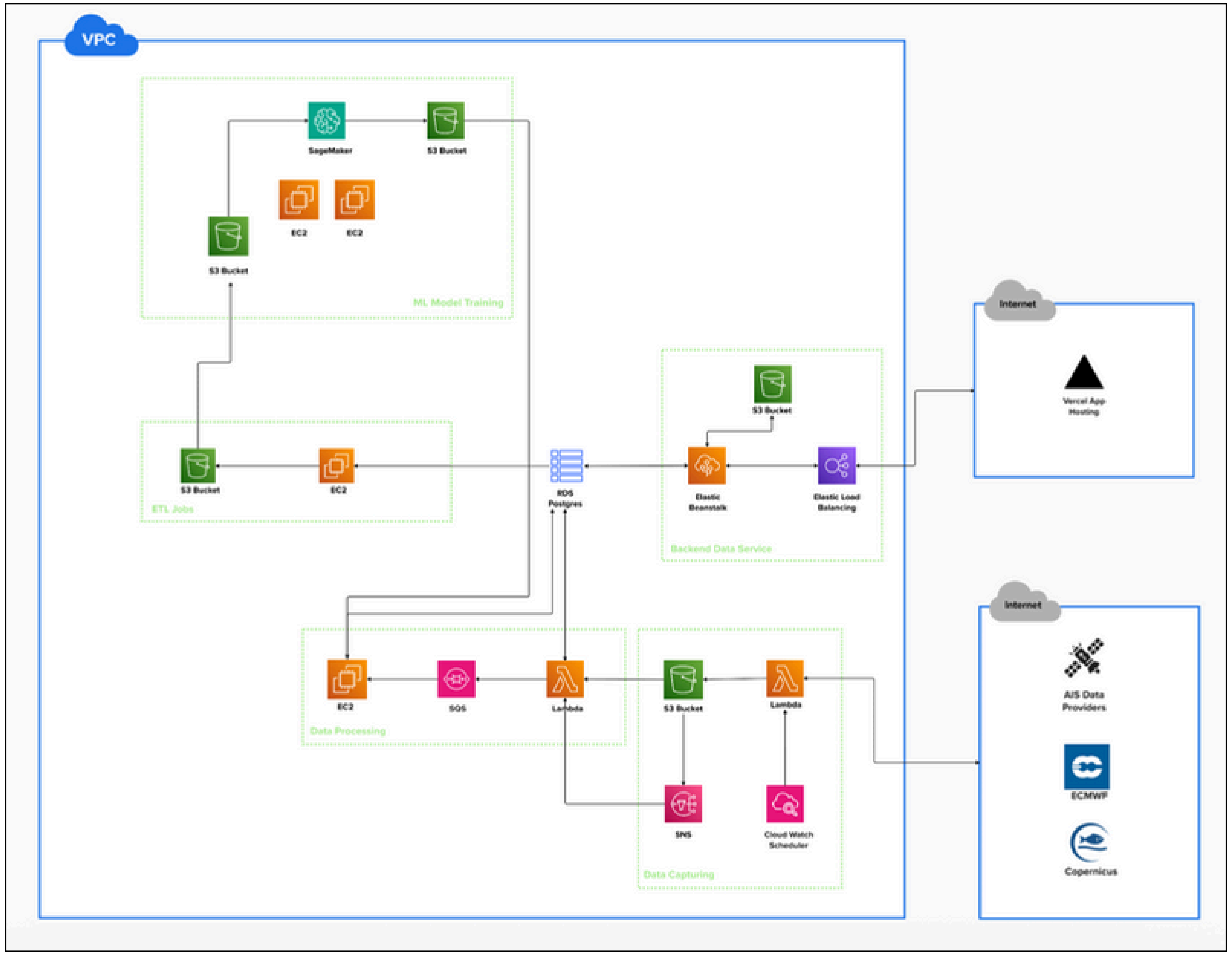

Inaccurate/Missing ETAs
Non-transparency in port operations
Delay in port services

Main Goals of the Project:

- Empowering Ports with Enhanced Decision-Making and Situational Awareness using AI
- A standalone web app that requires no additional hardware and no system access from ports
- A tailored solution for arrival prediction and not berth prediction

Key Insights and Results

System Architecture



Datasets

Historical AIS Data

Live AIS Data

Copernicus Weather Data (ERA5)

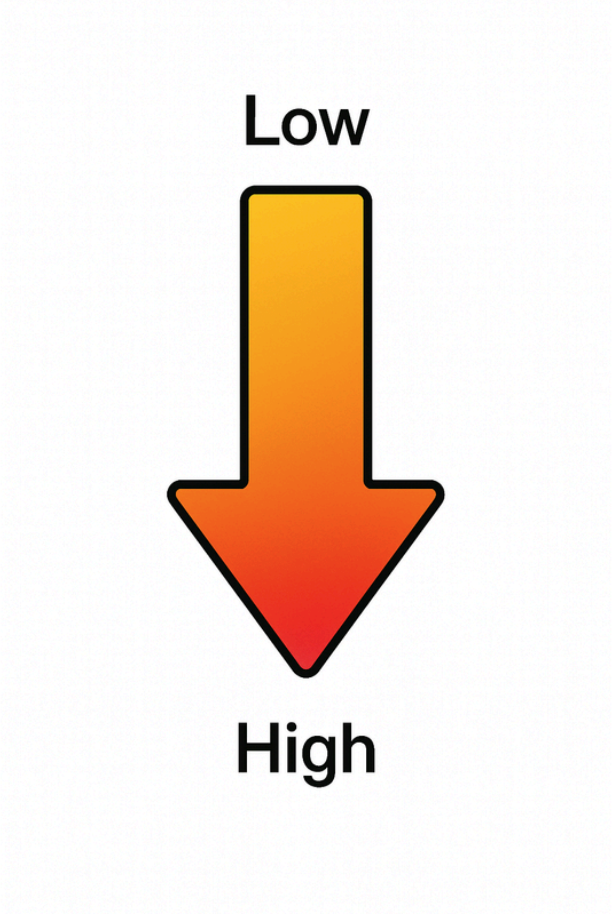
Shortname	Longname	Model	Units	Interval
10u	10 metre U wind component	ERA5	m/s	Hourly
10v	10 metre V wind component	ERA5	m/s	Hourly
mp2	Mean zero-crossing wave period	ERA5	s	Hourly
mwd	Mean wave direction	ERA5	deg (0 to 360)	Hourly
mwp	Mean wave period	ERA5	s	Hourly
pp1d	Peak wave period	ERA5	s	Hourly
swh	Significant height (wind waves and swell)	ERA5	m	Hourly
uo	Eastward sea water velocity	CMEMS	m/s	Daily
vo	Northward sea water velocity	CMEMS	m/s	Daily

Copernicus Marine Service

ECMWF

Algorithm Development

A combination modelling approach to achieve the highest possible accuracy in the last 6-48 hours prior to arrival.



Statistical Look-up Table

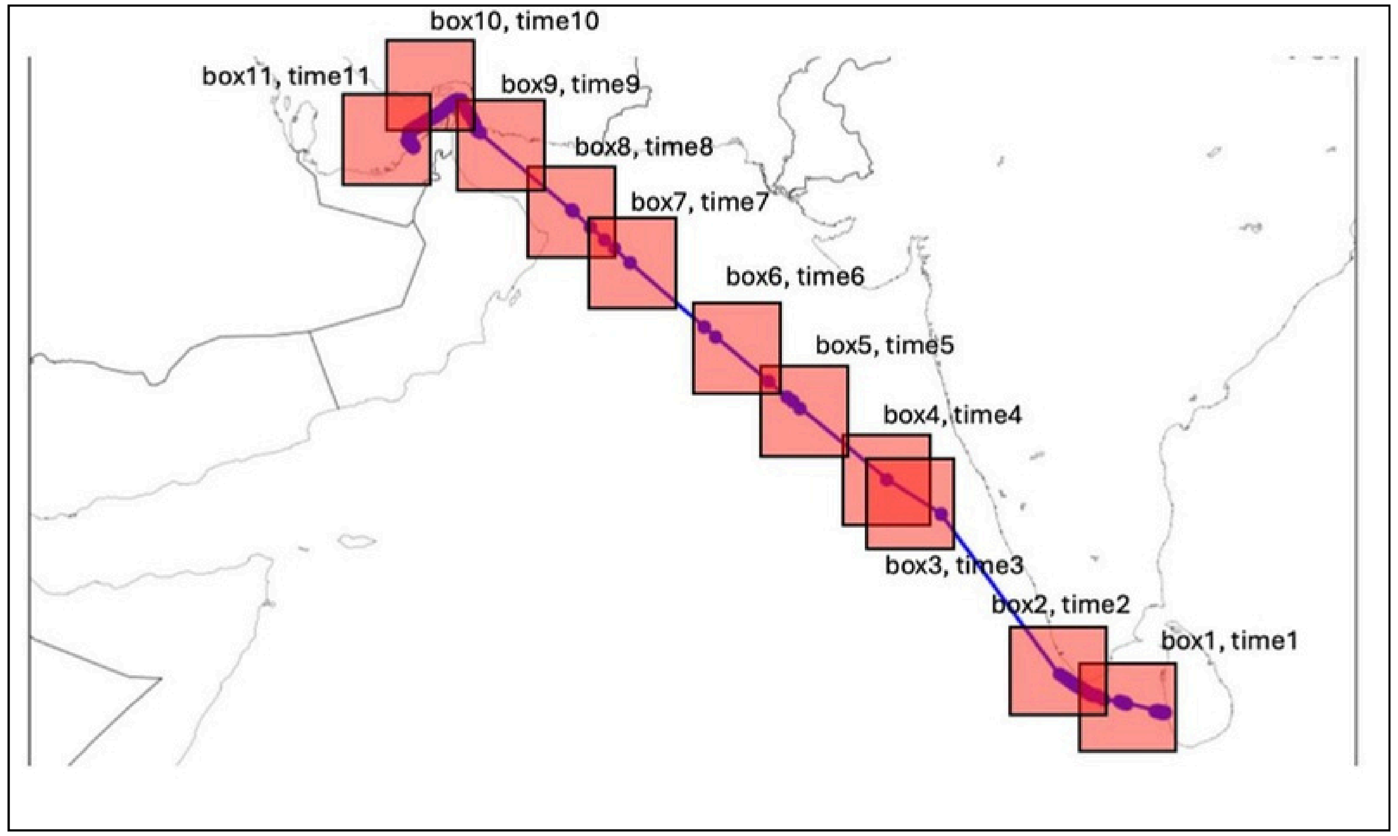
Gradient-based ML Models

Deep Network Model

Statistical Look-up Table

Statistical model based on the mean and median of all voyage's samples per point.

- Grid Points: Map area into grid points to facilitate localised analysis.
- Quantile Calculations: For each grid point, calculate the first (Q1) and second (Q2) quantiles of all AIS samples and features like:
  - Remaining Time to Arrival
  - Remaining Trajectory Distance
  - Speed
- A good fallback option



Statistical Look-up Table - Challenges & Outcomes

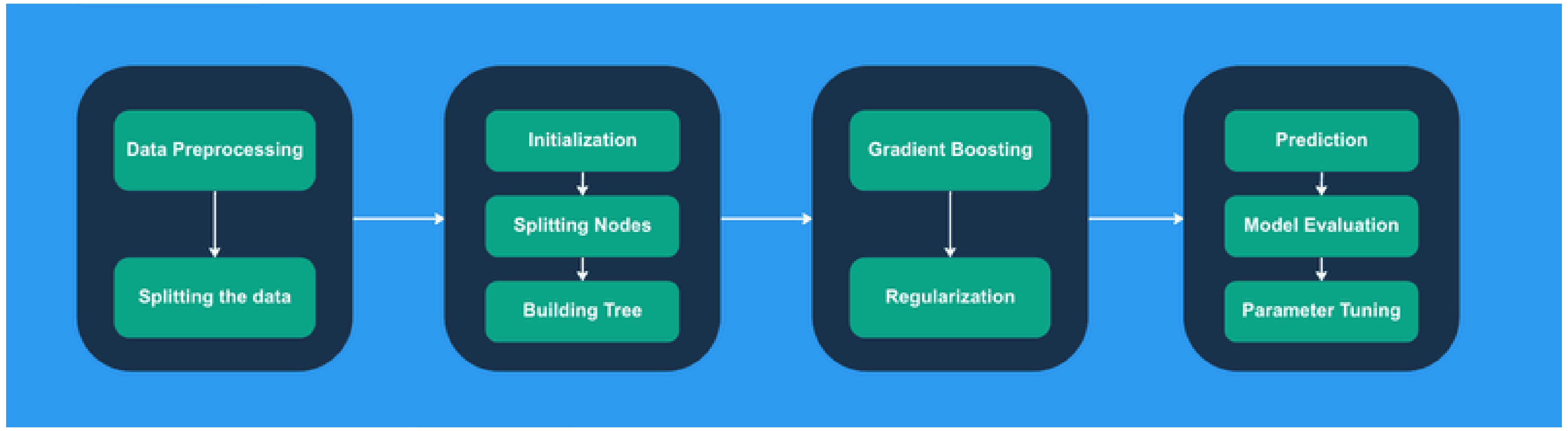
- Point-based prediction only
- Requires several pre-processing and clean voyages
- Low accuracy
- Data points are not available for every grid

Remaining Time Bins (hours)	Allowed Deviation (+/- X hours)	Reported ETAs (%)	Stat. Lookup Accuracy (%)
[0, 6]	1	22	92
[6, 12]	1	13	74
[12, 24]	2	9	73
[24, 48]	2	7	40

Gradient-based ML Models

Merged the ocean & weather data on both a one and five-degree grid level with each AIS update based on the latitude, longitude and timestamp.

- Point-based prediction and later area-based prediction
- Better accuracy than the previous method, but not excellent yet.
- Supported Seasonality features: Month and quarter based on the AIS timestamp.



Gradient-based ML Models - Challenges & Outcomes

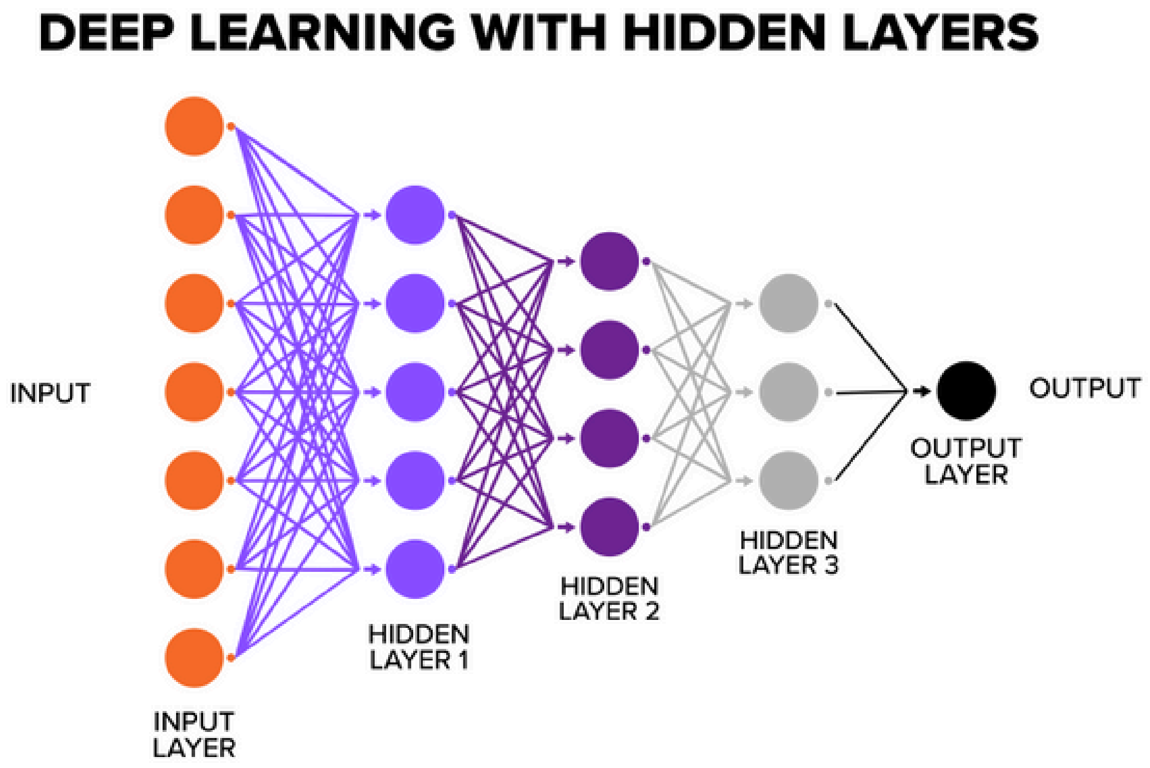
- Limitations on feature engineering and extracted features
- Require proper hyperparameters such as depth, pruning, early stop training, and so on.

Remaining Time Bins (hours)	Allowed Deviation (+/- X hours)	Reported ETAs (%)	Stat. Lookup Accuracy (%)	ML Model Accuracy (%)
[0, 6]	1	22	92	93
[6, 12]	1	13	74	84
[12, 24]	2	9	73	71
[24, 48]	2	7	40	57

Deep Learning Models

A deep neural network to predict the trajectory distances, which is used together with a speed estimate to calculate the remaining time.

- Allows a tokenisation method specific to this problem
- Best accuracy compared to previous approaches
- Performance depends on the amount of data, model size and training time



Deep Learning Model - Challenges & Outcomes

- Limitations on feature engineering and extracted features
- Require proper hyperparameters such as depth, pruning, early stop training, and so on.
- Finding Proper hyperparameters, such as model design, number of layers, each layer parameter, order of layers, and layer selection, is critical
- High model training cost for GPUs.

Remaining Time Bins (hours)	Allowed Deviation (+/- X hours)	Reported ETAs (%)	Stat. Lookup Accuracy (%)	ML Model+DL Accuracy (%)
[0, 6]	1	22	92	95
[6, 12]	1	13	74	91
[12, 24]	2	9	73	79
[24, 48]	2	7	40	57

Modelling Approach

Global Approach

- Works for all the major seaports across the globe
- Can be deployed in one hour
- Suitable for long-term predictions

Local Approach

- Highest level of customisation and localisations
- Requires retraining with local datasets
- Suitable for last-mile predictions

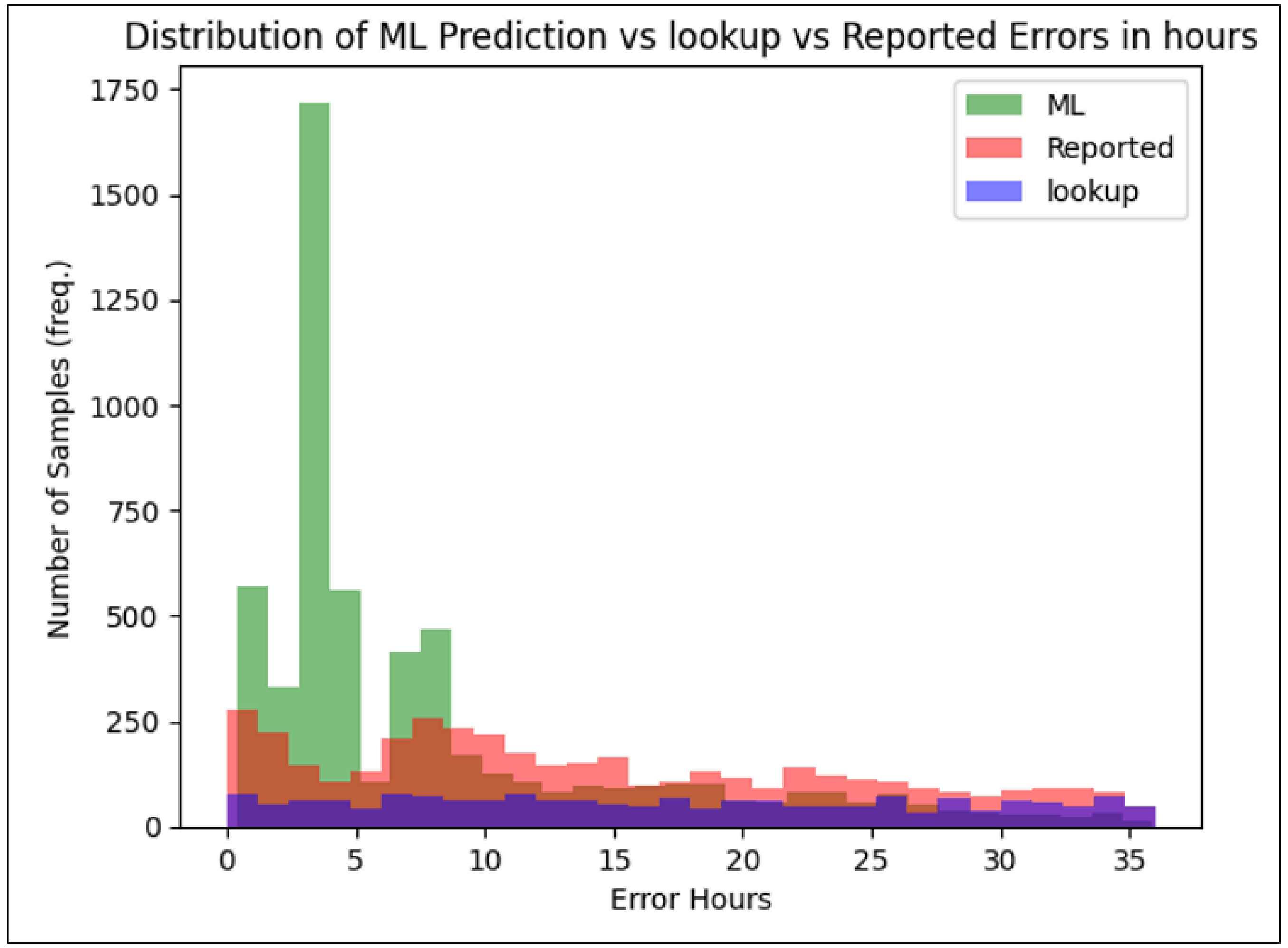
Pilot Test: Port of Algeciras, Spain

Puerto de Algeciras

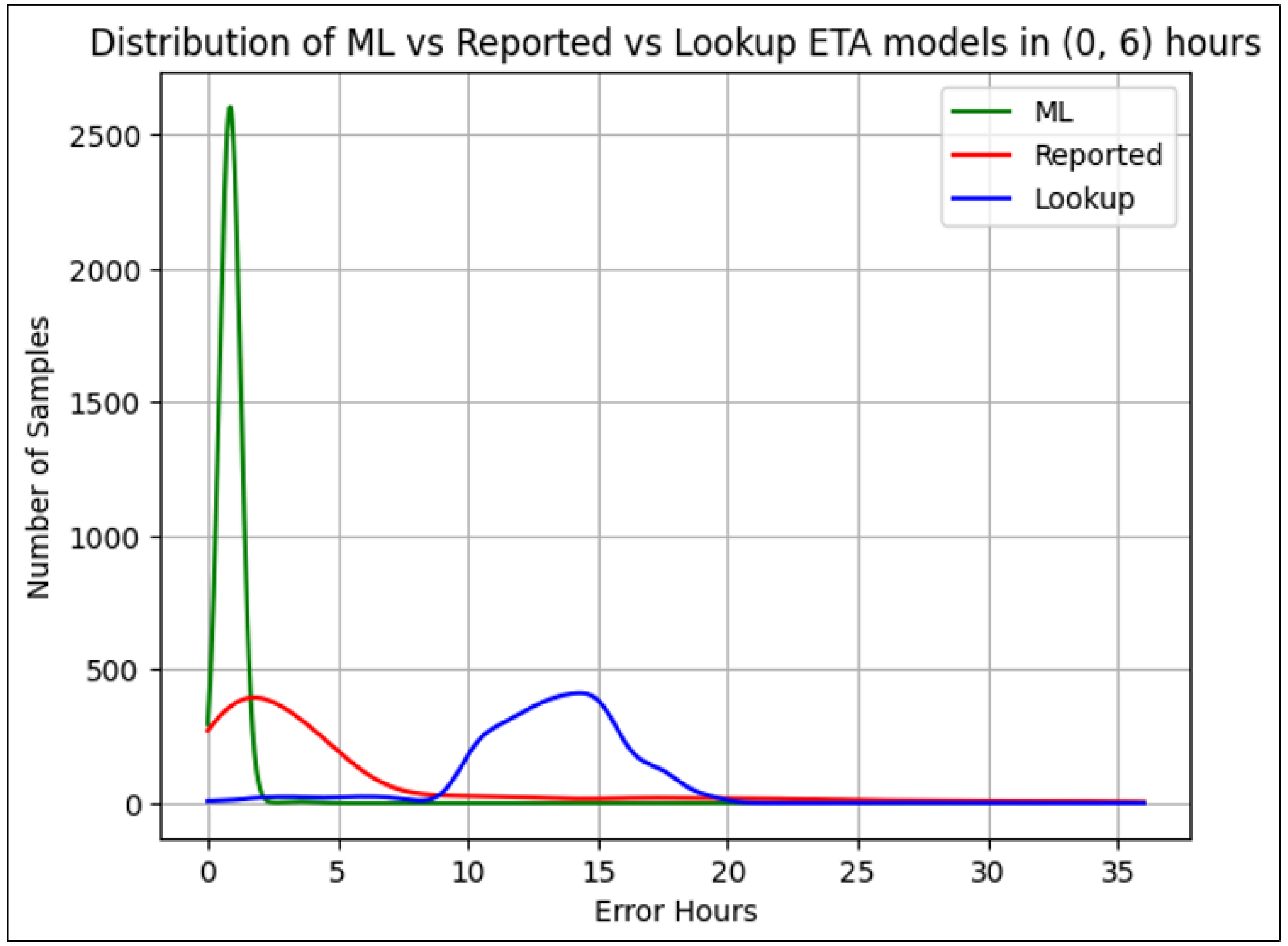
4 Weeks of testing in Dec 2024

Remaining Time Bins (hours)	Allowed Deviation (+/- X hours)	Reported ETAs (%)	Stat. Lookup Accuracy (%)	ML Model+DL Accuracy (%)
[0, 6]	1	22	92	95
[6, 12]	1	13	74	91
[12, 24]	2	9	73	79
[24, 48]	2	7	40	57

Pilot Test Results: Port of Algeciras, Spain

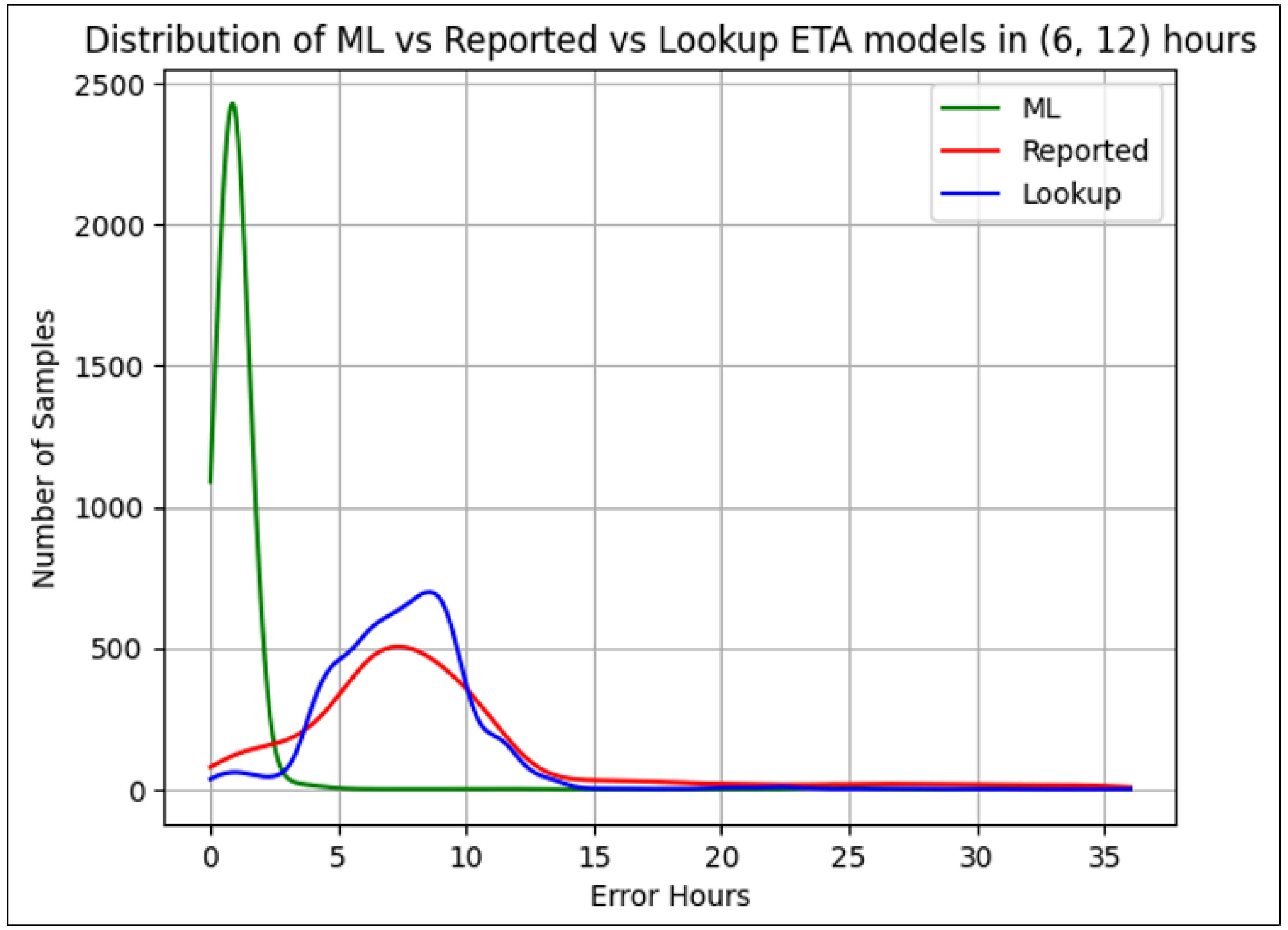


Distribution of overall errors around the mean for December 2024.

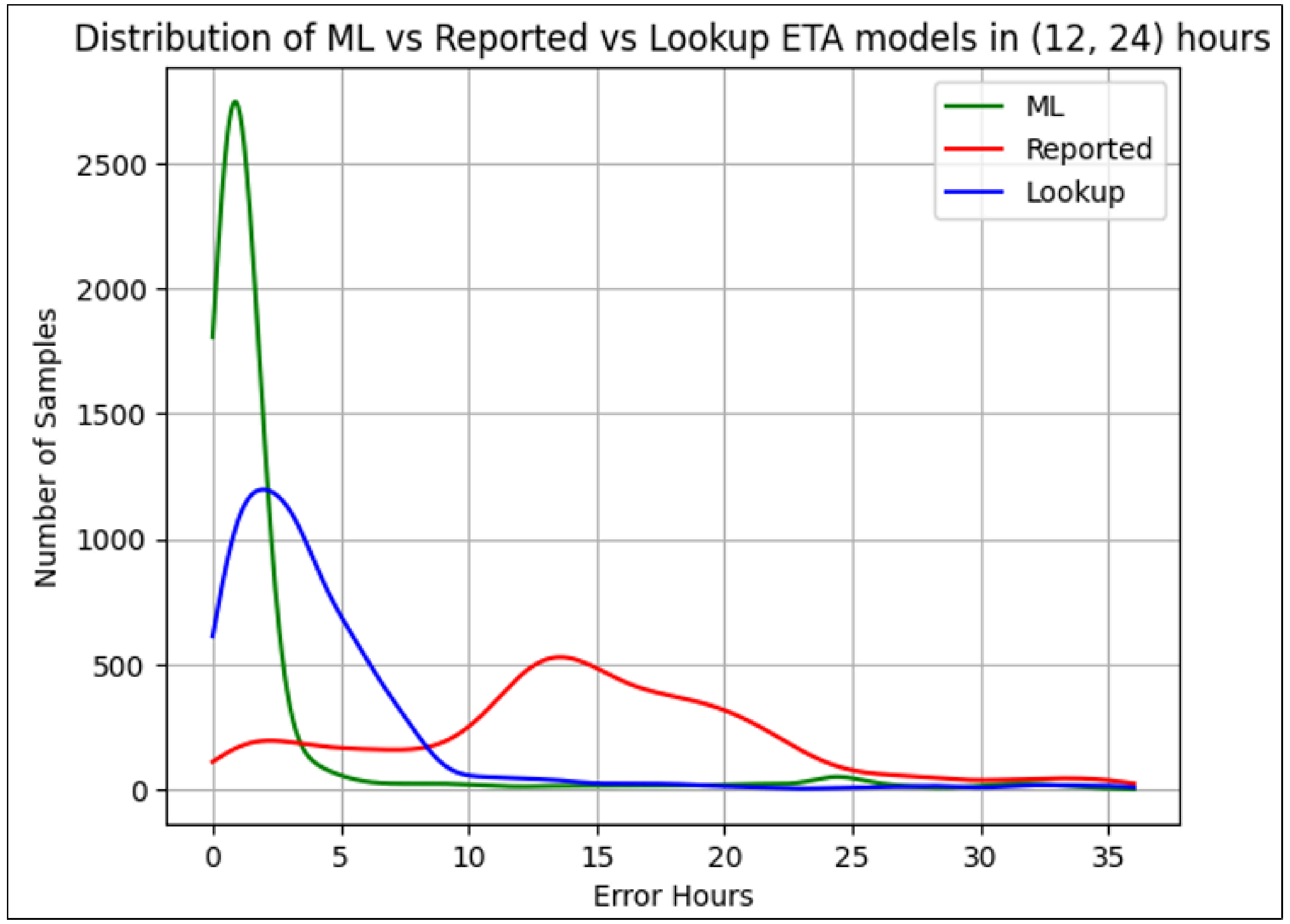


Distribution of errors around the mean for the 0-6 hours bin.

Pilot Test Results Continued...

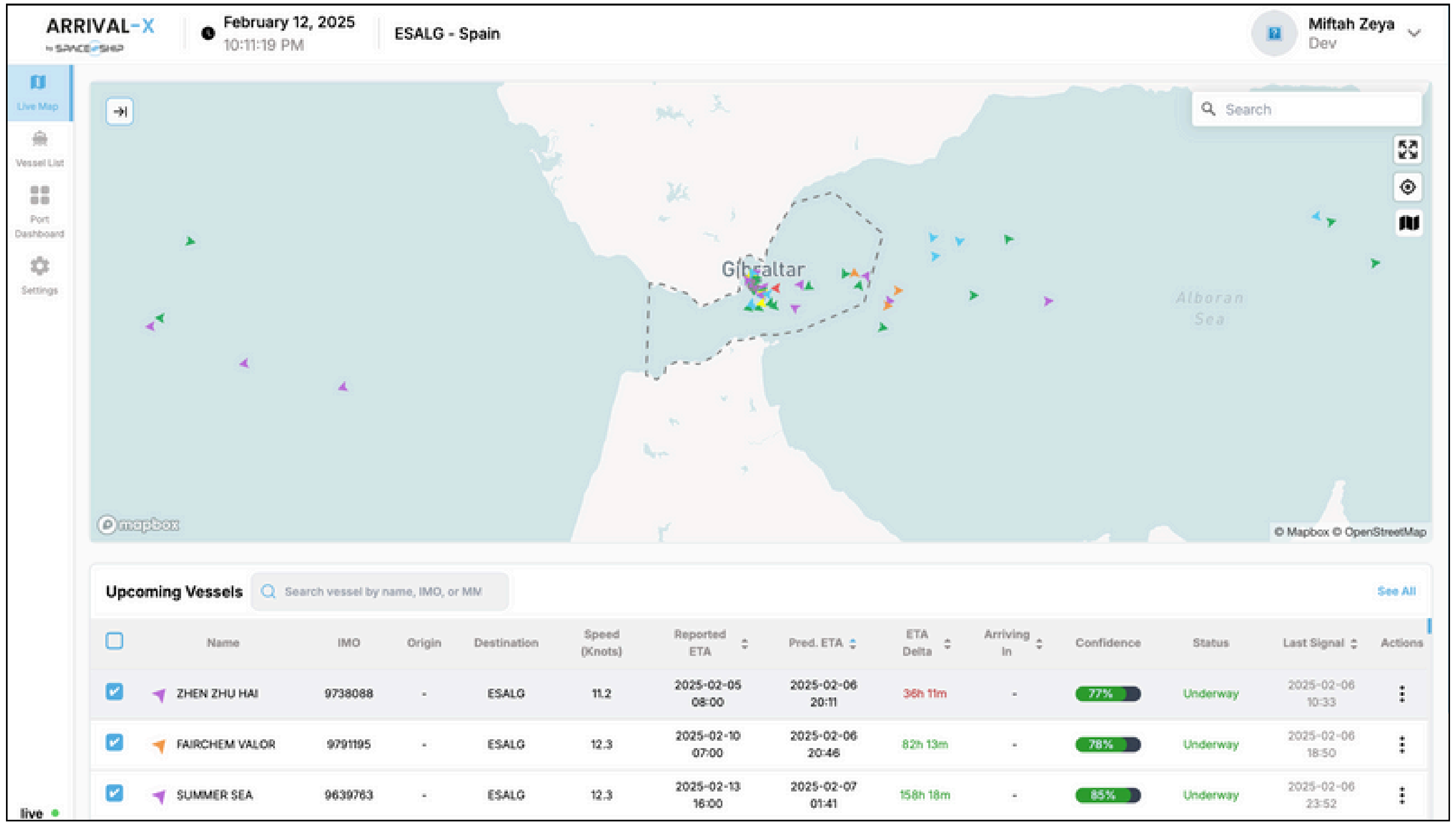


Distribution of errors around the mean for the 6-12 hours bin.



Distribution of errors around the mean for the 12-24 hours bin.

User Interface and Dashboard



Conclusion and Outlook

SPACE SHIP

Main Results

- All the project goals were achieved.
- Accuracy in the last 6 hours prior to arrival has outperformed expectations
- Weather data only plays a role in transoceanic voyages spanning multiple days
- A better quality of AIS data both in terms of accuracy and frequency can significantly improve the accuray in last 48 hours.

Future Work and Commercialisation

- Improvements in UI/UX as per pilot feedback
- Infrastructure scaling to support multiple users at the same time
- Refining the backend components to improve scalability
- Creating an API service as per the customer’s need
- Bug fixes for improved performance
- New pilot in June

Efficient supply chains contribute significantly to a nation's competitiveness, driving industrialization, sustainability and enhancing overall prosperity.

Thank You!

Demo?