DX and AX-Driven Low-Carbon Fleet Operation Technology for Maritime Decarbonization



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Challenges for Shipping Companies in Decarbonization

Tightening carbon regulations and supply-chain uncertainty are making maritime decarbonization more complex

CLEANER SHIPPING SAFER TRADE A MORE RESILIENT

Smaller shipping companies and nations face greater challenges in responding to escalating crises.



Regulatory Pressure

Stricter IMO / regional carbon rules
CII, fuel standards, emissions reporting

Compliance cost burden
Monitoring, verification, retrofit, carbon cost

Fuel transition uncertainty
LNG, methanol, ammonia, biofuels, future availability

Data and reporting complexity
MRV, DCS, lifecycle emissions, digital transparency

Investment and asset risk
Risk of stranded assets and technology lock-in

Operational Dilemma for Shipowners & Carriers

- Need to cut emissions while maintaining service reliability
- Need to invest under uncertain technology and policy pathways
- Need to optimize cost, schedule, fuel, and compliance at the same time
- Need better visibility and decision support across the fleet

Geopolitical & Supply Chain Pressure

War and geopolitical disruption
Route deviation, sanctions, security risk

Port congestion and unreliable schedules
Longer waiting time and disrupted port calls

Fuel and energy price volatility
Uncertain bunker and alternative fuel costs

Supply-chain fragmentation
Equipment shortages and unstable logistics networks

Demand uncertainty
Freight volatility and changing cargo flows

Main Difficulties in Real Operations

Uncertain voyage planning → Higher decarbonization CAPEX/OPEX → Difficulty securing green fuel → Higher risk of schedule disruption → Complex emissions compliance decisions → Reduced confidence in long-term investment

What This Means

- Decarbonization decisions become slower
- Operational risk increases
- Cost exposure rises
- Digital and AI-based decision support becomes essential

DX and AX for Just-in-Time Arrival Voyage Operation

Integrated approach to meet tightening maritime decarbonization requirements

CLEANER OCEANS
SUSTAINABLE SHIPPING
BRIGHTER TOMORROW

DX (Digital Transformation)

Builds the digital foundation: connect, collect, standardize, visualize

DATA CONNECTS THE OCEAN

- **Ship Sensors & Noon Reports** — Engine, fuel, position, etc.
- **AIS / Voyage Data** — Location, speed, route, etc.
- **Weather & Ocean Data** — Wind, wave, current, etc.
- **Port / Terminal Data** — Berth schedule, congestion, terminal operation, etc.

Data Integration Platform → **Standardized Data Flow** → **Digital Twin & Monitoring Dashboard**



DX = Data visibility and connectivity

+

AX = AI-driven prediction and optimization

→ **Combined =** Operational decarbonization through Just-in-Time arrival

AX (AI Transformation)

Adds intelligence: predict, optimize, recommend, act

AI TURNS DATA INTO ACTION

- **Optimal Voyage Operation Model** — Finds optimal speed and route considering weather, port condition and regulations
- **Port Waiting Time Prediction Model** — Predicts port congestion and berth availability
- **Ship CO2 Emission Prediction Model** — Estimates CO2 emissions under various operating conditions

- **Scenario Simulation** — Evaluate multiple options
- **Prescriptive Optimization** — Identify best operation plan
- **Autonomous Recommendation** — Real-time decision support

Integrated JIT Arrival Engine

- Synchronizes vessel ETA with berth readiness
- Optimizes speed and fuel use
- Minimizes waiting time and CO2 emissions

- **Recommended Speed Profile** — Optimal speed over voyage
- **Dynamic ETA Update** — Real-time ETA adjustment
- **Berth Coordination** — Synchronize with port/terminal
- **Fuel & CO2 Reduction** — Lower fuel use and emissions
- **Higher Schedule Reliability** — On-time arrival and stable operation

REAL-TIME DATA
INTELLIGENT DECISIONS
GREENER VOYAGES



Key Outcomes

for a Decarbonized Maritime Future

- **Lower Port Waiting Time** — Less idle time at anchor
- **Lower Fuel Consumption** — More efficient operation
- **Lower CO2 Emissions** — Support net-zero targets
- **Smarter Fleet Operation** — Higher efficiency and resilience

5 Stages of AX for Low-Carbon Operation

From digital foundation to autonomous AI-driven decarbonized operations

DATA TODAY
CLEANER TOMORROW

CLEANER OCEANS
SMARTER SHIPPING
A SUSTAINABLE TOMORROW

LOW-CARBON
CONNECTED
AUTONOMOUS

DX Digital Transformation (Builds the foundation)

AX AI Transformation (Adds prediction, action and autonomy)

1 Data Foundation (DX)

Builds the trusted data base

Ship sensors (IoT)
AIS / voyage data
Engine data
Weather & ocean data
Port / terminal data
Fuel & emissions data
Cloud / Data Lake (Trusted Maritime Data)

- Data collection
- Integration & standardization
- Data governance
- Connectivity
- Real-time data pipeline

2 Digital Twin (DX)

From data to virtual representation



- Real-time monitoring
- Vessel / route / port twin
- Simulation environment
- What-if analysis
- Operational visibility

3 Prediction AI (AX)

From current state to future insights

AI Models (Predictive Intelligence)

- Fuel consumption prediction
- CO_2 / GHG emission prediction
- ETA prediction
- Port waiting time prediction
- Weather-routing prediction

- Forecasts future conditions
- Predictive analytics
- Risk and delay prediction
- Emission prediction

4 Physical AI (AX)

From insights to real-world action



- Speed optimization
- Route optimization
- Energy management
- Closed-loop control
- Execution in real operations

5 Agentic AI (AX)

From single-vessel optimization to autonomous orchestration



- Autonomous decision support
- Fleet-wide coordination
- Multi-objective optimization
- Compliance-aware planning
- Continuous adaptation

Expected Outcomes

- Lower fuel consumption
- Reduced CO_2 emissions
- Just-in-time arrival
- Higher schedule reliability
- Smarter fleet operation

DX builds visibility and structure; AX adds prediction, action, and autonomy.

TOWARDS A NET-ZERO MARITIME FUTURE

Just-in-Time Arrival (JIT): Concept and Benefits

Converting port waiting time into productive voyage time through AI-powered ship–port coordination

CLEANER OCEANS
SMARTER SHIPPING
A SUSTAINABLE TOMORROW

Rush and Wait (As-is)

Ship rushes to arrive early and waits at anchorage due to port congestion



Voyage time
= distance / sailing speed

Waiting time
= ATA – Original RTA

AI based JIT (GMDRT, to-be)

Adjusts voyage timing with AI-powered ship–port data exchange to arrive just in time



Voyage time
= distance / sailing speed

Waiting time
= Changed RTA – Original RTA = 0

Assumption

What if port waiting time could be converted into voyage time through an AI-powered ship–port data exchange model?



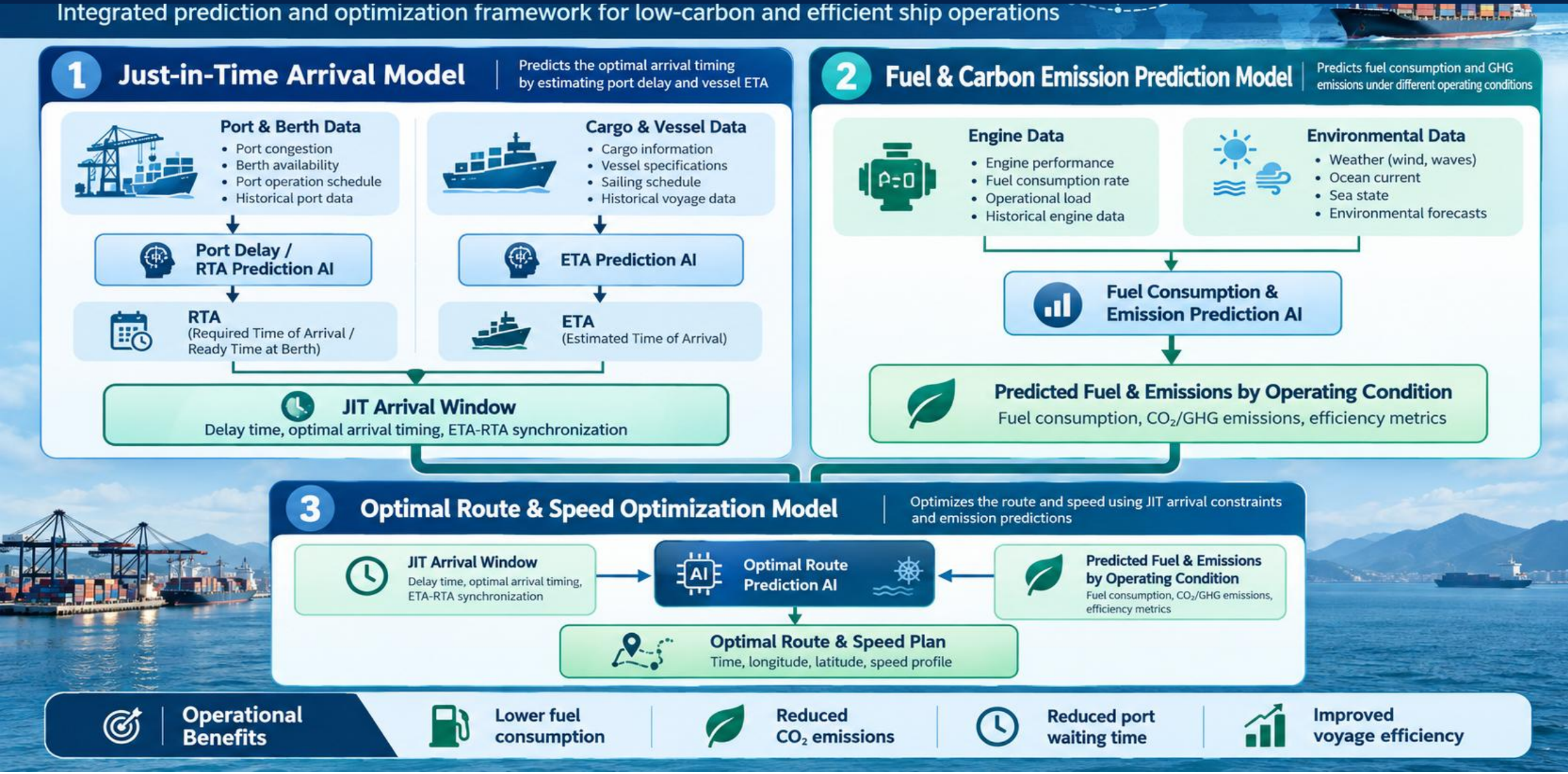
Key Benefits

- Lower CO_2 emissions
- Reduced anchorage waiting
- Optimized speed profile
- Improved schedule reliability

Lower Fuel Consumption ↓ | **Reduced CO_2 Emissions** ↓ | **Less Port Waiting Time** ↓ | **Smarter JIT Coordination** ↑

GMDRT Project: AX Transformation

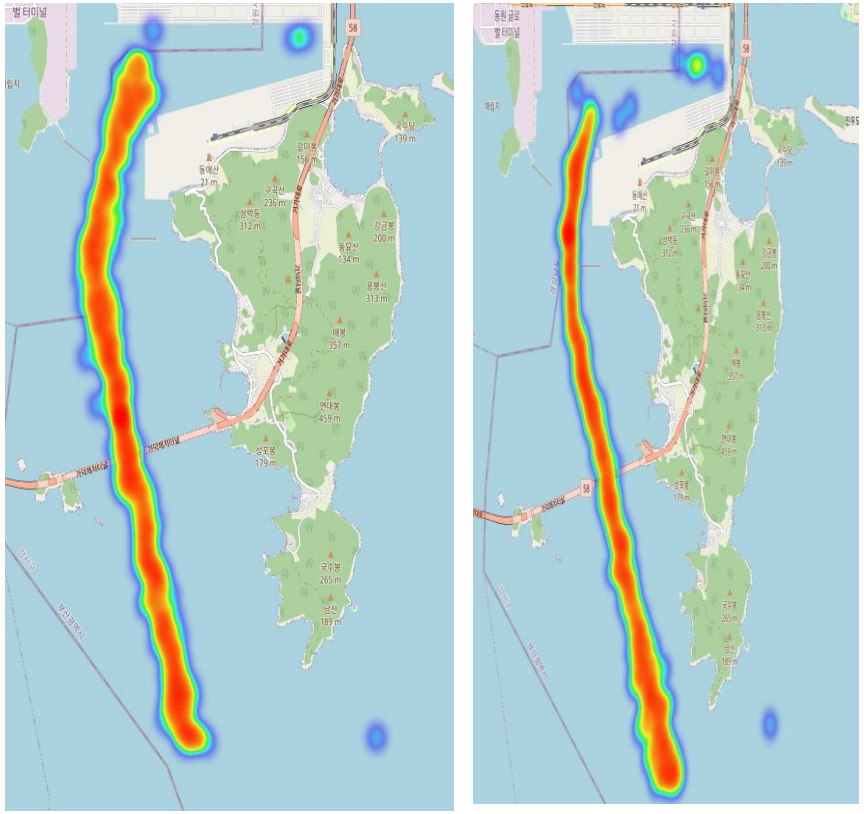
Integrated prediction and optimization framework for low-carbon and efficient ship operations



DX : Digital Transformation

- Ship Route Tracking – Route Modeling Basis data from AIS data

Approaching and Departure Intensity Map



Representative Approaching and Departure Data

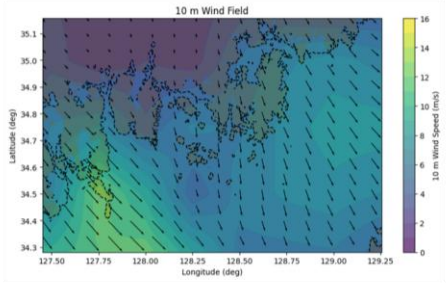


DX : Data Foundation

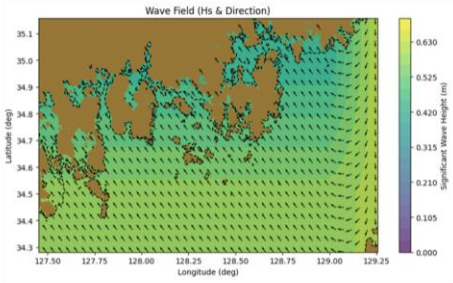
- **Vessel Schedule Planning**
  - Source: TOS(Terminal Operating System) of PNIT, Busan New Port
  - Attributes: Terminal code, Year of arrival, Voyage number, Assigned berth, berthing side, ATB, ATD, Discharge and load cargo volumes, etc.

- **Terminal Operation Planning**
  - Source: Busan New Port
  - Attributes: Terminal code, Year of arrival, Voyage number, Work time, Discharge and load cargo volumes

- **Weather Information**
  - Source: ASOS (Automated Synoptic Observing System), Korea Meteorological Data Portal
  - Attributes: Precipitation, Wind speed, Wind direction, Humidity, Visibility, Solar radiation, Sunshine duration



2023년 12월 경 바람 분포



2023년 12월 경 파도 분포

DX : Berth Delay Data

Terminal Initial Dataset

{v(callsign), b(berth), s_v (start_time), d_v(end time), cargo id, yard stack plan}

선석	선사	모선항차	선사항차	Head(Bridge)Stern	선명	ROUTE	반입마감시한	접안(예정)일시	출항(예정)일시	양하	적하	Shift	AMP	상태
T1(P)	MSC	MSGN005	HW543R/HW547A	02 (14) 19	MSC GINA	PERTWI	2025-11-21 20:00	2025-11-22 07:00	2025-11-23 05:00	959	1503	2	N	DEPARTED
T3(P)	MSC	MELA001	GY546A/GY546A	43 (50) 63	MSC EMILIA	ALPACA	2025-11-22 03:00	2025-11-22 13:00	2025-11-23 12:00	0	2125	0	N	DEPARTED
T2(P)	MSC	MSRA001	UK545A/UK545A	22 (37) 42	MSC RANIA	CHINKE	2025-11-22 08:00	2025-11-22 18:00	2025-11-24 00:00	1123	1266	0	N	DEPARTED
T1(P)	MSC	MNGR002	GY547A/GY547A	02 (08) 19	MSC NIGERIA	ALPACA	2025-11-22 21:00	2025-11-23 07:00	2025-11-24 11:00	664	1361	8	N	DEPARTED
T3(P)	MSC	MFRT031	HT547R/HT548A	46 (55) 57	MSC FORTUNE F	SRISEA	2025-11-23 04:00	2025-11-23 14:00	2025-11-24 08:00	432	370	0	N	DEPARTED

Berth Planning +RTA Prediction

{s_v,v_length,v_height,v_port_starboard}

```
berthingplan = sortrows(berthingplan,'ETA',"ascend")

% terminal
% %length/depth/tons/draft
terminallength = 1000
terminaldraft = 100
terminaldepth = 100
terminaltons = 5000000

% constraints
i=1
for kk=1:40
    if terminallength>vessel.VSSL_LT(kk) && terminaldraft>vessel.VSSL_DRFT(kk) && terminaldepth>vessel.VSSL_DP(kk) && terminaltons>vessel.GRTG(kk)
        vessel(i,:) = vessel(kk,:);
        i = i+1;
    end
end
```

DX : Ship Operation Data Measurement



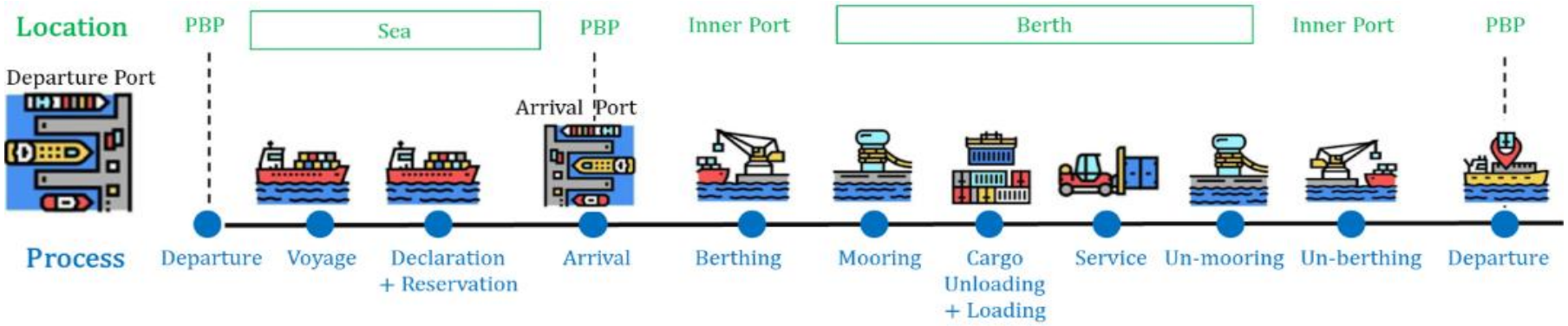
LAT	LON	heading	wind_speed (m/s)	Total Fuel(Kg)
30.4061	-81.546	306.4217	4.478488	311.943
30.40617	-81.5462	127.4791	4.478488	320.8556
30.4061	-81.5461	239.8975	4.478488	329.7683
30.4061	-81.5461	349.1504	4.420515	320.8556
30.40613	-81.5461	289.5277	4.420515	329.7683

- *Carbon Emission = Carbon Factor X Fuel, Fuel(ton)= △ fuel X time*
- *△ fuel = Break Power(Actual engine operating power) X Specific Fuel Oil Consumption*
- *Break Power = Effective Power X Efficiency factors(η_{hull} $\eta_{propeller}$ η_{shaft} transmission efficiencies)*
- *Effective Power = Total Resistance X Ship Speed*
- *Total Resistance = Hull resistance(friction, form, wave-making)*

  + Environmental effects(wind, waves, current)

  + Appendages (fins) + Fouling

DX : Data Exchange

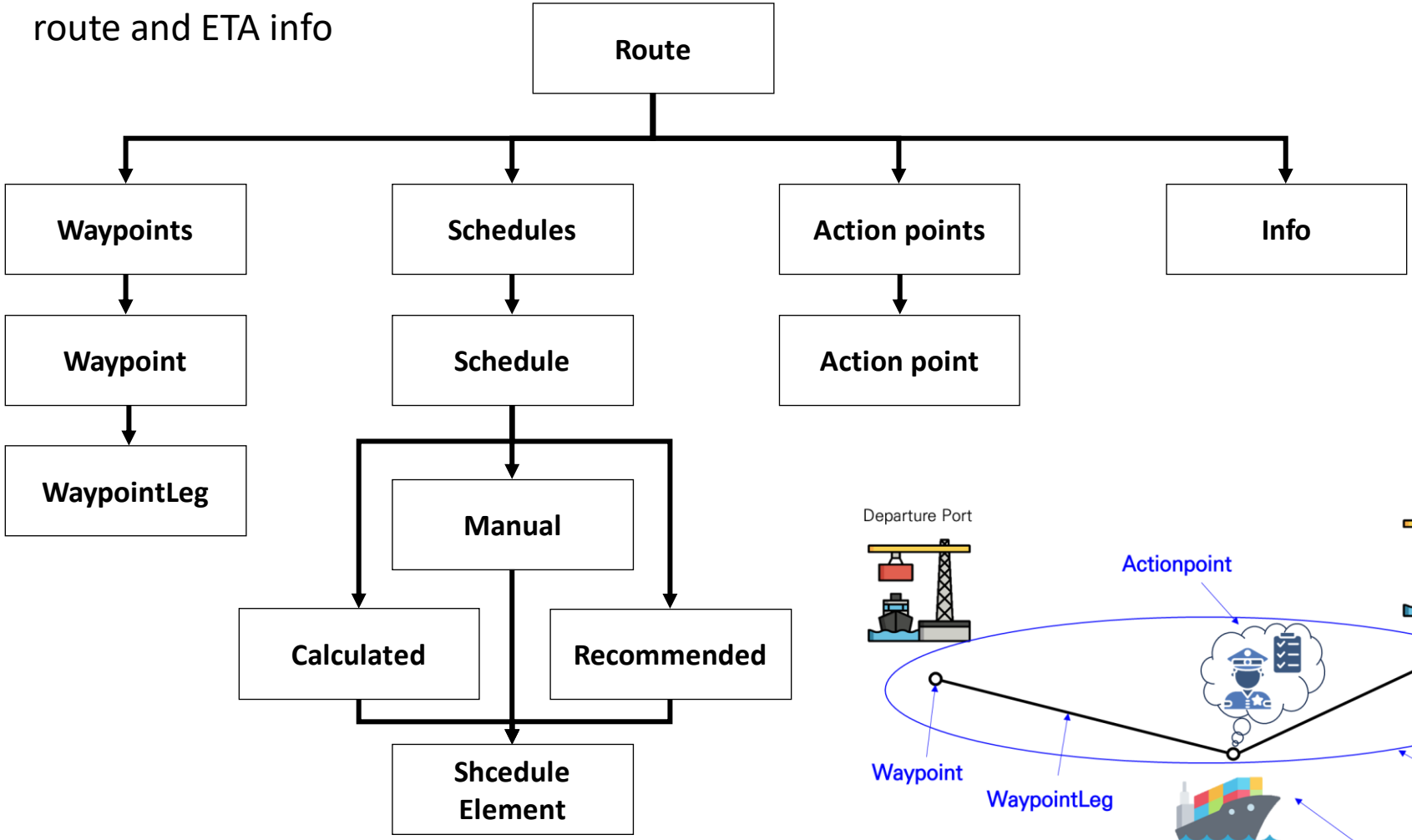


- IMO FAL Convention and SVD(Ship Voayge Data) Model

Process	Data (IMO SVD)
Departure	port of departure(111,112)por of arrival (108, 109)PBP Name (231)PBP location (xxx)Berth Name (232) Berth Location(xxx) ATA(63),ATD(65),ETA(541),ATA(540) ,ETA PBP (XXX),ATA PBP (XXX) voyage number (191)voyage leg identifier (605)ship poisiton latitude (0602)ship position longitude(0602)shi p reporting date time (603)
Voyage	voyage leg identifier (605), Distance through water (612), distance to next port (615) speed through water (616),speed through water (616),course over ground (332) ship heading (620),draught (357),draught forward, aft (621, 622) reason for ship deviation (607),position deviation, latitude(608),position deviation, longitude(609) ship deviation start date time(610),ship deviation stop date time (611) FUEL(0882),TOTALCO2(0883)

DX : Data Exchange

- S-421 Model which is Electronic Chart Display Chart Standard can be a proper model to route and ETA info



AX : Fuel and CO_2 Prediction (ML for CO_2 Emission Estimation)

Black Box Model

- **Data Driven Method**
- **Measured Fuel = operational data**
- ***Fuel ($\dot{m}_f$)=f(speed, heading, weather..)***
- **Accuracy 92~99%**

Navigation					M/E F.O.C
Speed	Obs. Distance	Course	Wind	B.F	LSFO
-	-	-	-	-	0.00
11.43	8.00	167.00	-	-	0.00
5.77	60.00	334.00	-	-	0.00
-	-	-	-	-	0.00
15.00	36.00	215.00	-	-	0.00
-	-	-	-	-	0.00
-	-	-	-	-	0.00
6.92	9.00	195.00	-	-	0.00
18.10	257.00	11.00	15.00	4.00	0.00
22.18	122.00	11.00	15.00	4.00	0.00
8.44	27.00	267.00	-	-	0.00

Grey

White Box Model

- **Resistance → Power → Propulsion Efficiency → Fuel Consumption**
- **Based on model test data**
- **Accuracy 95% (in calm water conditions)**



AX : Black Box Model (ML for CO_2 Emission Estimation)

- **Model Objective**

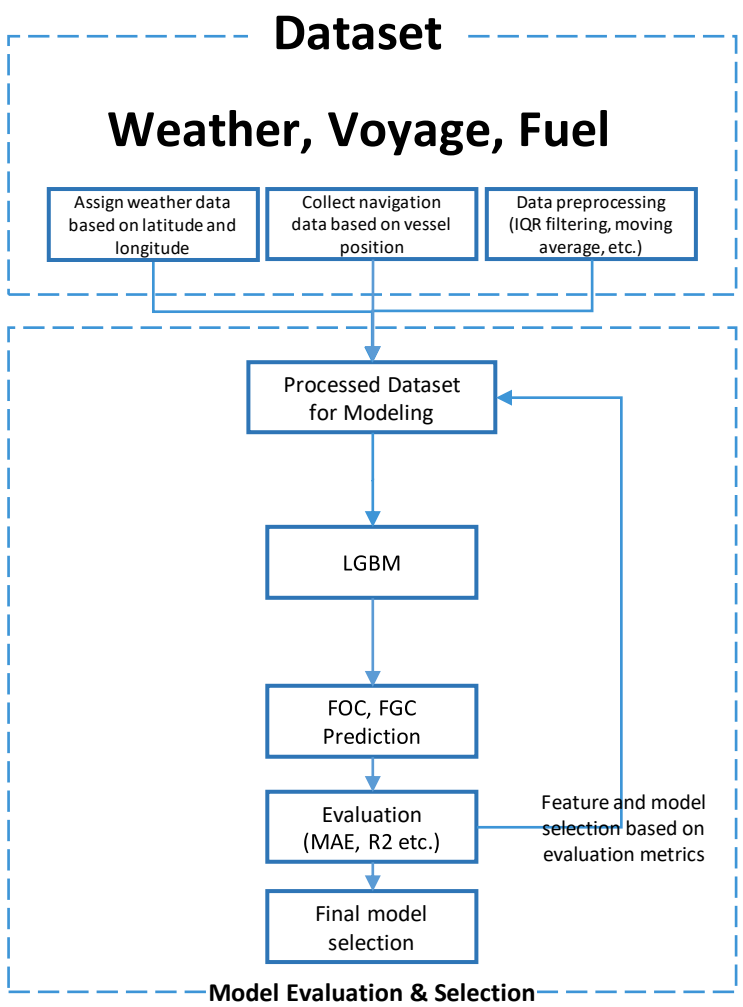
  : Predict hourly fuel consumption based on operational and environmental time-series data.

- **Model Configuration**
  - Algorithm: Transformer Encoder
  - Input features: speed over ground, heading, wind direction, wind speed, significant wave height, wave period, wave direction
  - Output: Hourly fuel consumption at time t (kg/h)

- **Definition of the Fuel Consumption Cost Term**
  - $F(R, v_t)$: hourly fuel consumption

AX : Black Box Model (ML for CO_2 Emission Estimation)

- Modeling Workflow



Model Training and Selection Approach

Candidate Model Examples

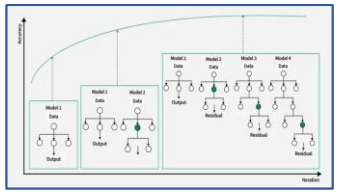
[LGBM (Light Gradient Boosting Machine)]

Gradient Boosting Framework

Sequentially trains multiple decision trees to reduce prediction errors

Each tree learns from the residuals of the previous model

Optimizes performance through a leaf-wise growth strategy



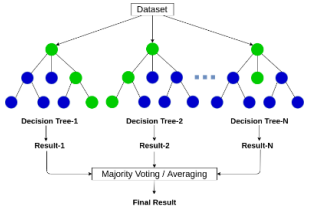
[Random Forest Regressor]

Ensemble Learning

Builds multiple decision trees using random sampling

Each tree is trained independently

Final prediction is determined by averaging



Evaluation metrics

MAE (Mean Absolute Error)

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i|$$

R2-Score

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2}$$

MAPE (Mean Absolute Percentage error)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - \hat{Y}_i}{Y_i}\right|$$

RMSE (Root Mean Squared Error)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\|y(i) - \hat{y}(i)\|^2}{N}},$$

AX : Black Box Model (ML for CO_2 Emission Estimation)

- AI Model Performance

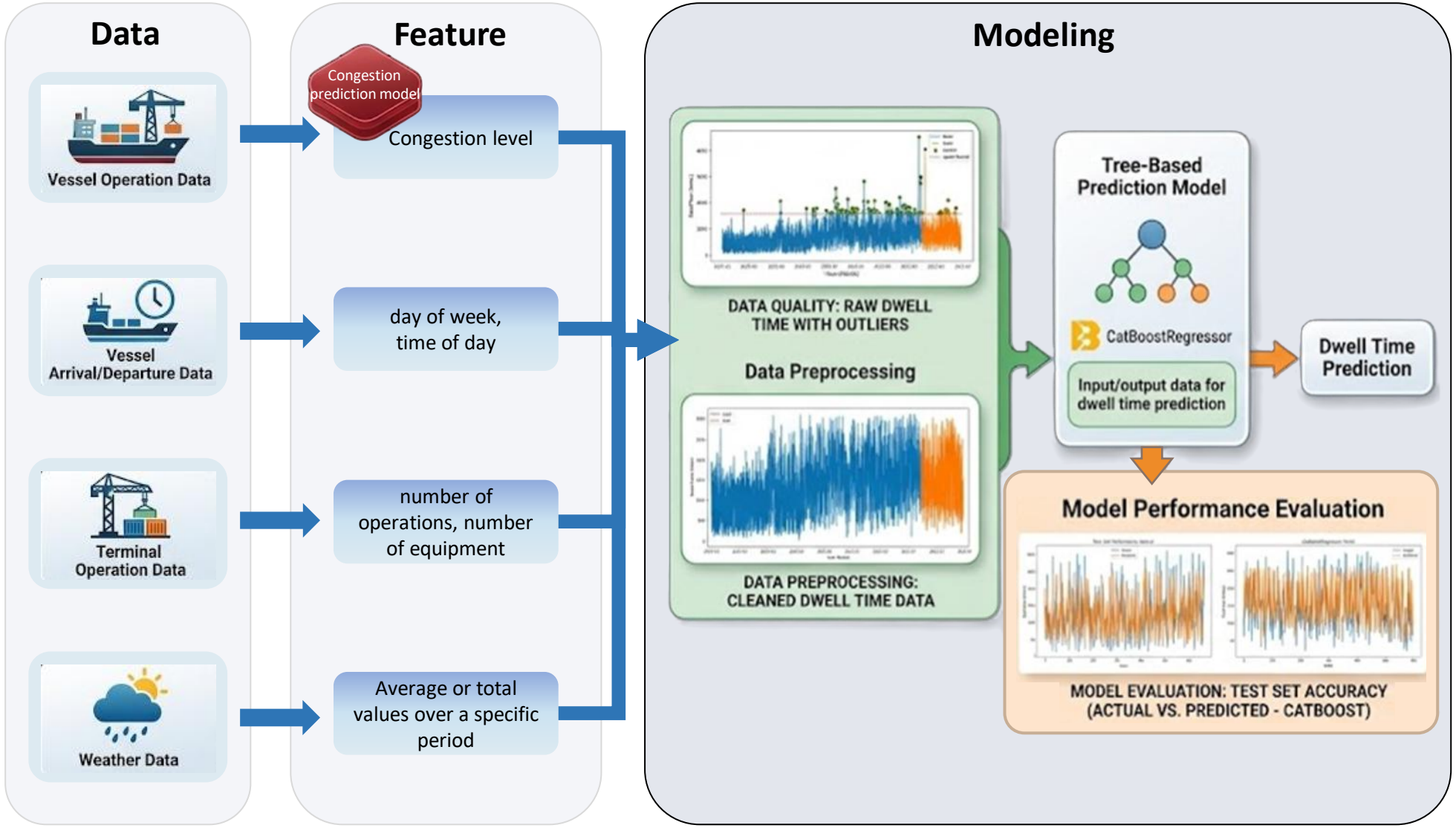
R2-Score	**0.9258**
MAPE	0.1163
RMSE	32.2836
MAE	25.4735



- Evaluation Metrics for Four Models

Dataset	**Case 1 - Bulk**	**Case 2 23000TEU Container**	**Case 3 174K LNGC**
Model	LGBM	Transformer	Transformer
R2-Score	0.9256	0.9505	0.9072
MAPE	0.1165	0.0538	0.0083
RMSE	33.0664	1512.6225	28.0900
MAE	25.3714	1063.5222	17.3914

AX : Machine Learning for Berth Delay



AX : Machine Learning for Berth Delay

- Model Objective

  : Predict port dwell time using machine learning to generate the RTA constraint value.

- Model Configuration
  - Algorithm: gradient boosting regressor(ensemble regression)
  - Input features: number of handled containers(load/unload), wind speed, air temperature, humidity, air pressure, water temperature
  - Output: predicted dwell time → operation start time + dwell time → RTA

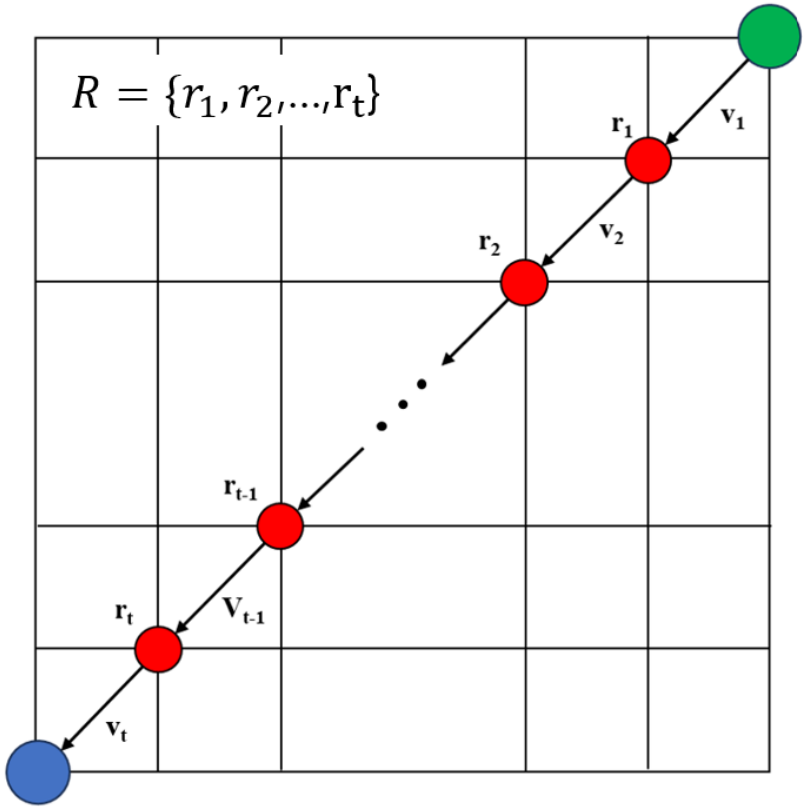
- Definition of the Time-Related Cost Term
  - $T(R, v_t)$: *(Estimated vessel arrival time) − (Operation start time + dwell time)*

AX : Reinforcement Learning for Route Optimization

- Key Objective

  : This is a multi-objective decision-making problem

  - Minimization of fuel consumption
  - Meeting the Required Time of Arrival (RTA)
  - Maintaining navigational safety

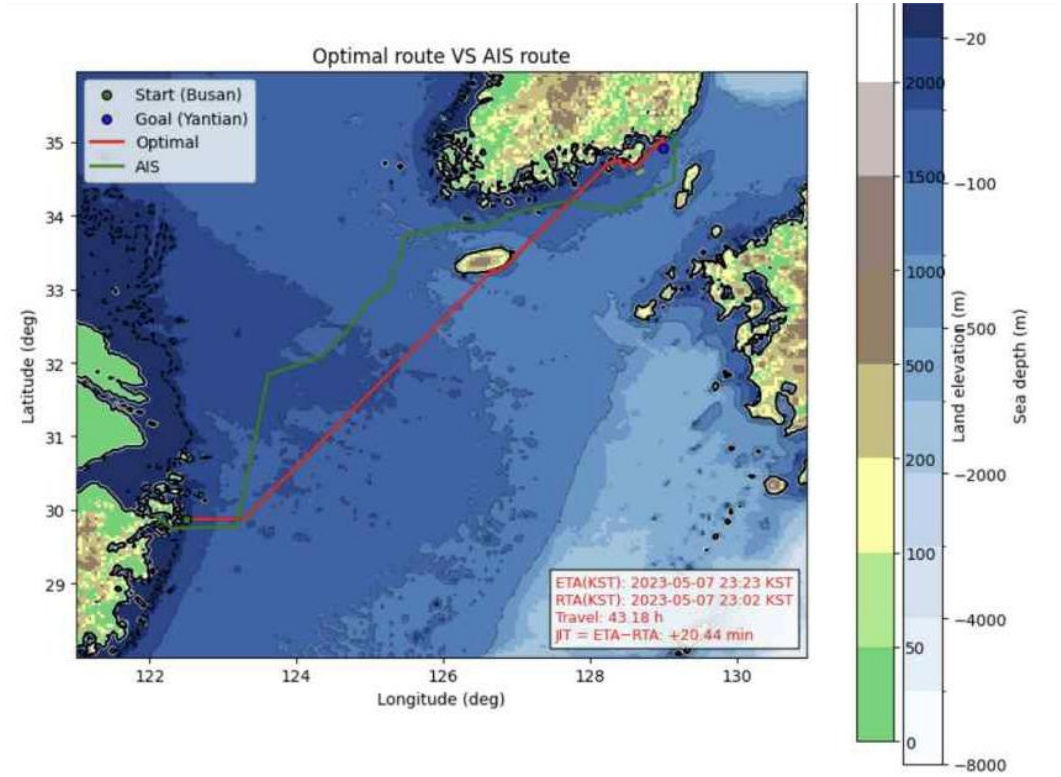


- Objective Function

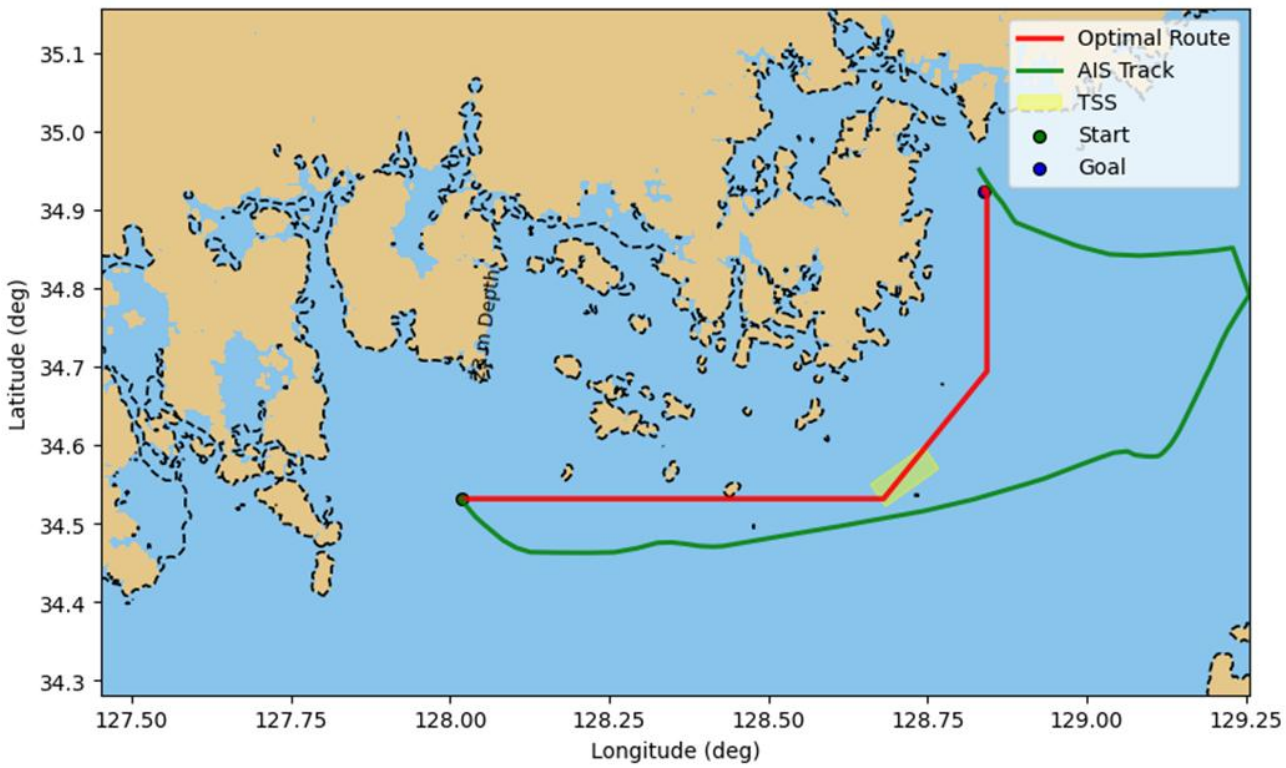
$$\min J = \alpha F(R, v_t) + \beta T(R, v_t) + \gamma F(R, v_t)$$

  - F(R, v_t): Fuel consumption cost term (Fuel Cost)
  - T(R, v_t): Time-related cost term (Time Penalty)
  - S(R, v_t): Safety-related cost term (Safety Constraint)
  - α, β, γ: *Weighting factors for each term (adjusting the importance of fuel, time, and safety)*

AX : Reinforcement Learning for Route Optimization

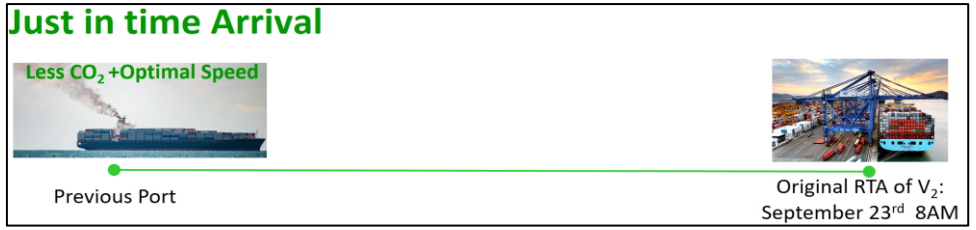


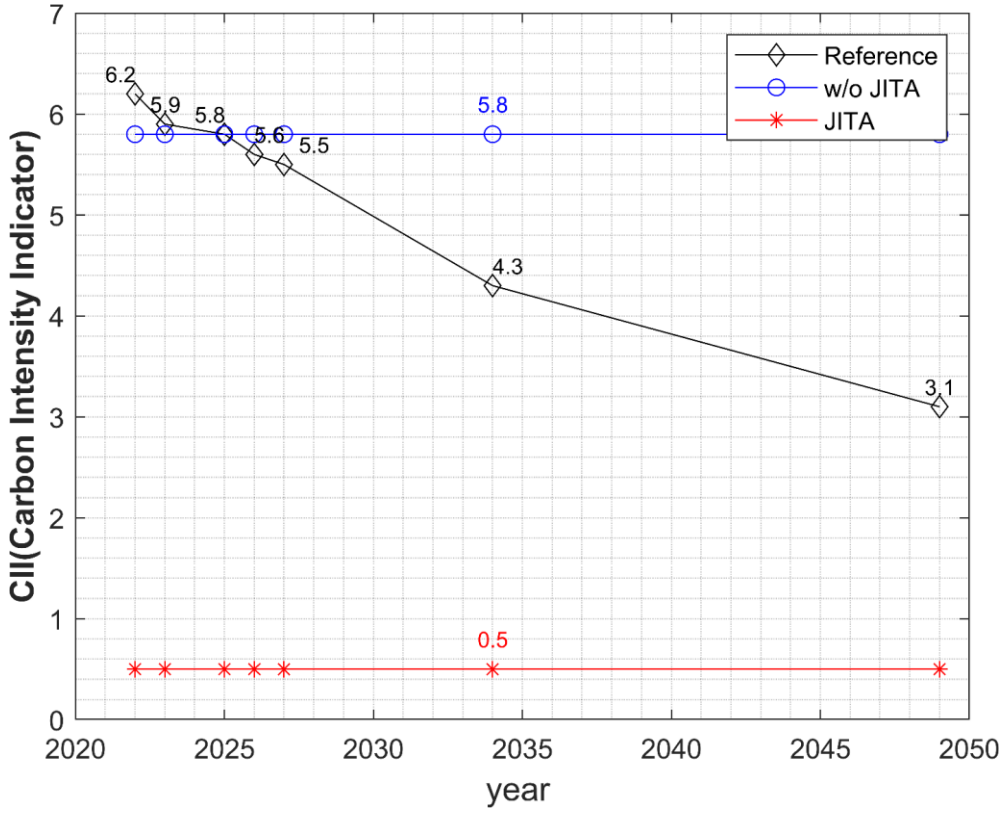
Vessel	ETA	RTA	JIT
OSAKA VOYAGER	2024-05-01 22:53 KST	2024-05-01 22:58 KST	5.54 min

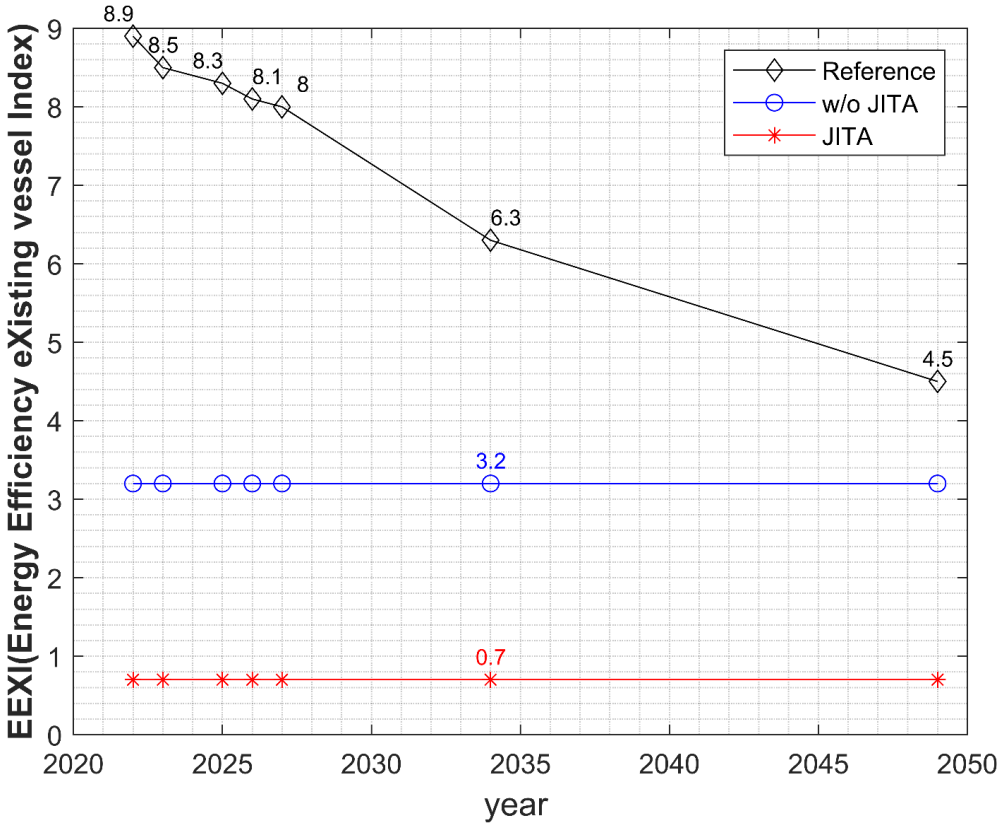


GHG	Quantity Assessment
Fuel Reduction	10.0 ton reduction
CO_2 Reduction	11.32% reduction

AX : Low Carbon Fleet Operation







Conclusion: DX and AX for Low-Carbon Voyage Operation

Key takeaways for maritime decarbonization and AI-enabled ship–port collaboration



1 Decarbonization-Driven Voyage Optimization Is No Longer Optional

As international decarbonization regulations continue to tighten, low-carbon voyage operation enabled by DX and AX has become essential.

- IMO — Regulations & IMO targets
- CO_2 — Carbon reduction
- Voyage optimization
- Compliance pressure
- CII improvement
- Fuel savings



2 AX Requires a Strong DX Foundation

AI transformation can only be realized when data collection, integration, standardization, and digital visibility are already in place.

DX Builds the foundation → **AX** Adds intelligence and drives action

Data Foundation	Digital Twin	Prediction AI	Low-Carbon Operation
• Sensor data • Ship / voyage data • Port data • Weather & ocean data • Fuel & emissions data	• Data integration • Standardization • Real-time monitoring • Visualization • Operational visibility	• Fuel consumption prediction • CO_2 / GHG prediction • ETA prediction • Weather routing • Risk forecasting	• Optimized routing • Speed optimization • Energy management • Real-time decision • Autonomous support



3 AI Agents Enable Coordinated Low-Carbon Operation

Low-carbon operation can be achieved through coordinated AI agent models for ships, carriers, and ports. The GMDRT Project demonstrated implementation and validation, confirming visible carbon reduction and CII improvement.

Ship AI Agent	Carrier / Fleet AI Agent	Port AI Agent
• Voyage optimization • Speed & energy management • Real-time decision support	• Fleet optimization • Vessel coordination • Emission management	• Port call optimization • Berth allocation • Terminal operation coordination



- CO_2 Emissions Reduced
- Fuel Consumption Reduced
- CII Improved
- Better Ship–Port Coordination

DX builds the foundation. **AX turns data into coordinated low-carbon action.**

- Lower CO_2 Emissions
- Improved CII Performance
- Smarter Voyage Operation
- Higher Operational Reliability

Thank You

Q&A

Toward a Sustainable and
Intelligent Maritime Future

CLEANER OCEAN
SMARTER OPERATIONS
A SUSTAINABLE TOMORROW

