Harbor tug transit fuel consumption optimization

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Outline

- Background, Motivation & Objective
- Methodologies & Technologies
- Toolkits Development
- Summary & Future Exploration

Background & Motivation

IMO GHG Reduction Strategy

MPA goal: net-zero emissions for port operators by 2050

2023	2030	2050	~2100
Carbon intensity reduction ~40%	Carbon intensity reduction ~70%	Phase out GHG	

Green Harbour Craft Technologies	Ocean-going Vessel Green Technologies
Operation Optimisation	**Cleaner Energy/Fuel**

Operation Optimisation

- Fuel consumption optimisation
- Consolidate services
- Better carbon estimator/indicators

Cleaner Energy/Fuel

- Low-carbon/Zero-carbon fuel
- Wind/Current/Solar energy
- Electrification

https://shipnerdnews.com/comply-with-eexi-cii-in-the-upcoming-years/

Objective & Target Value

Motivation/Objectives/Deliverables

Motivation: Trends toward cleaner port environments and enforcement by new imposed legislations lead to economic pressure on vessel operators. It is essential to develop energy saving/emission reducing methods for higher fuel efficiencies and lower emissions.

Objective: Develop harbour tug transit-phase fuel consumption optimisation solutions to reduce fuel consumption and emission of harbour tugs.

Deliverables: 1) Actionable insights and recommendations for fuel saving and emission reduction; and 2) A toolkit for optimizing vessel speed patterns and transit routes

Value / Benefits

- The fuel efficiency of harbour tugs can be improved, and operating costs reduced
- Higher fuel efficiencies would result in lower emissions
- As a whole contributing to decarbonization and meeting legislative requirements

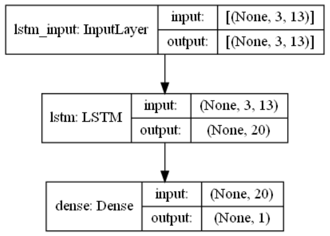
A Holistic Picture of Methodology

AI Modeling

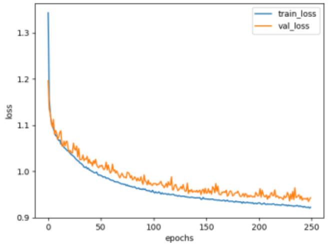
Prescriptive analytics
Fuel consumption estimation & optimisation and decision support

Reinforcement learning based fuel consumption optimisation

Learn based fuel consumption prediction



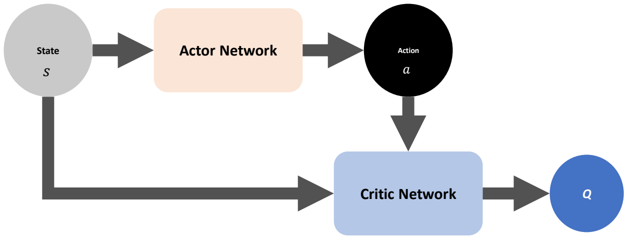
Model structure

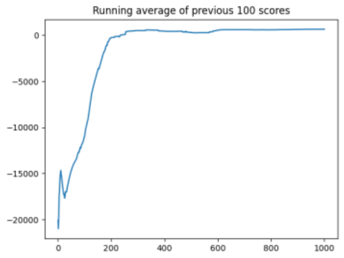


Training/validating curves

Reward

RL based fuel consumption optimisation model (route and speed band)





Operation state extraction

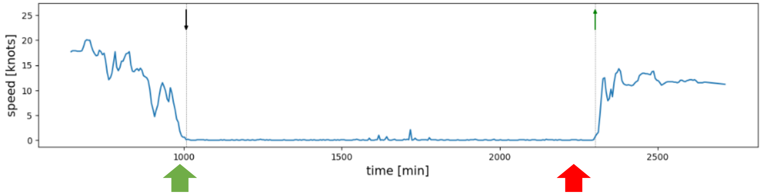
Transit based fuel consumption analytics

explainability

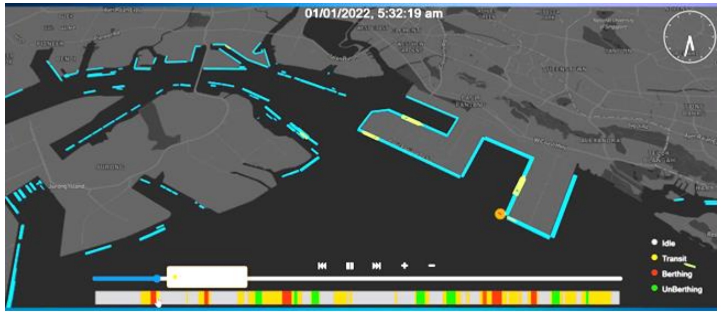
Data-Driven Analytics

Descriptive analytics
Factors impacting fuel consumption

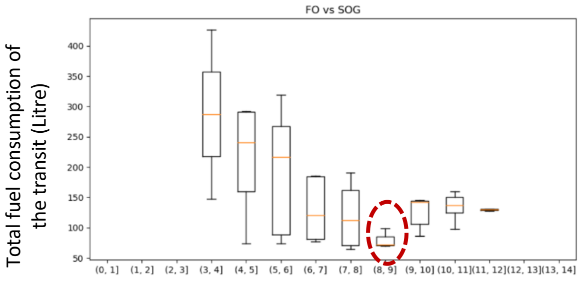
Harbor tug operation state extraction



Start of mooring **End of mooring**

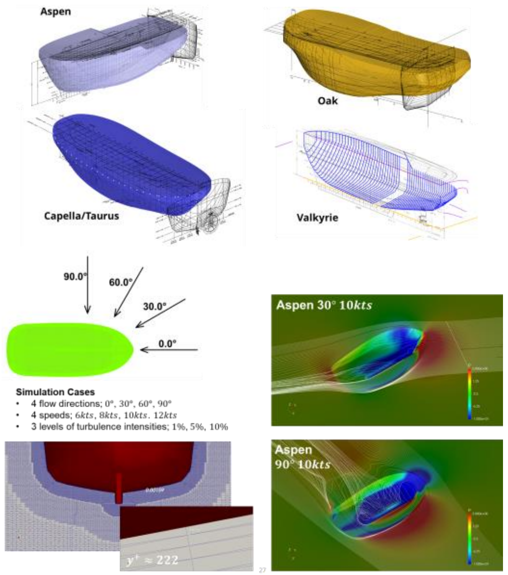


Transit pattern extraction & analytics



Transit Average speed band (Knot)

CFD simulation for Harbor tug



Our work has been accepted/presented in the 33rd International Joint Conference on Artificial Intelligence (IJCAI)

CREATING GROWTH, ENHANCING LIVES

Multisource Data Processing

Correlating multiple sources data

Multisource data

1 Processed machinery data

2 Sounding record

3 Manufacturer testing record

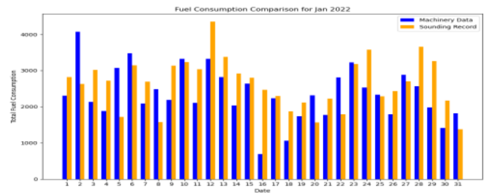
Comparison studies

Comparison of daily sounding record with machinery data

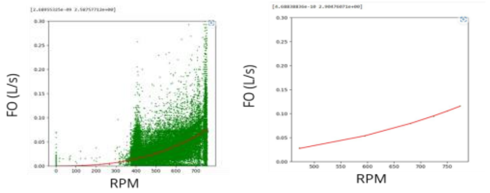
Comparison of machinery data with manufacturer testing results

Theoretical models – engine fuel consumption curve etc.

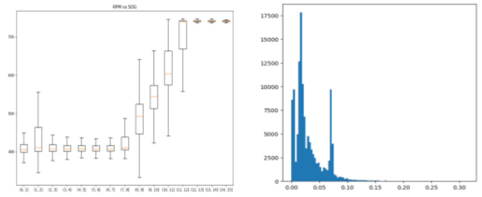
Insights & Observation



Comparison analytics



Fuel consumption profile

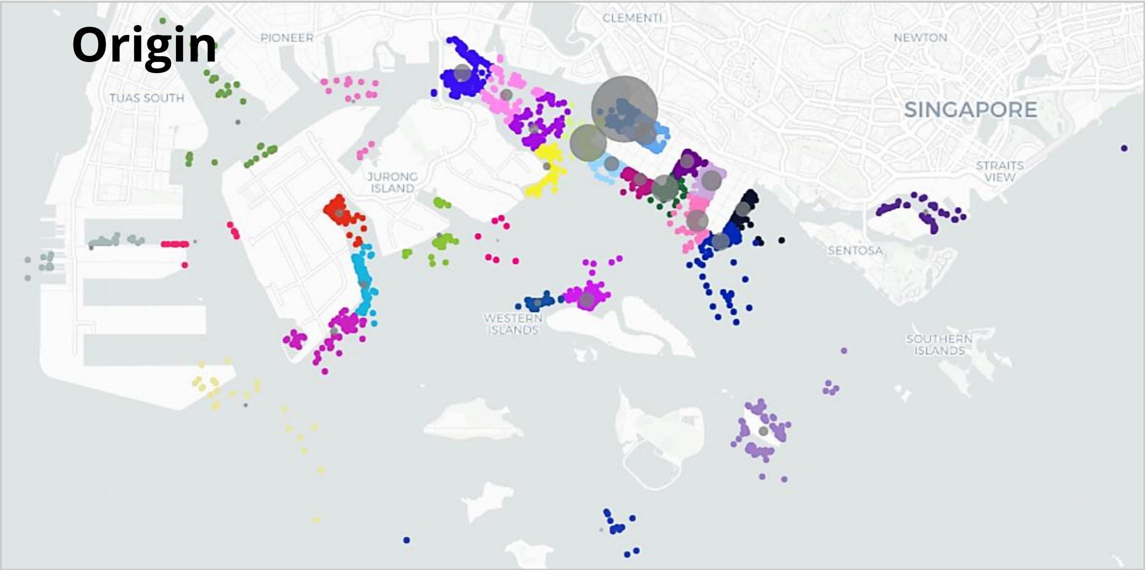


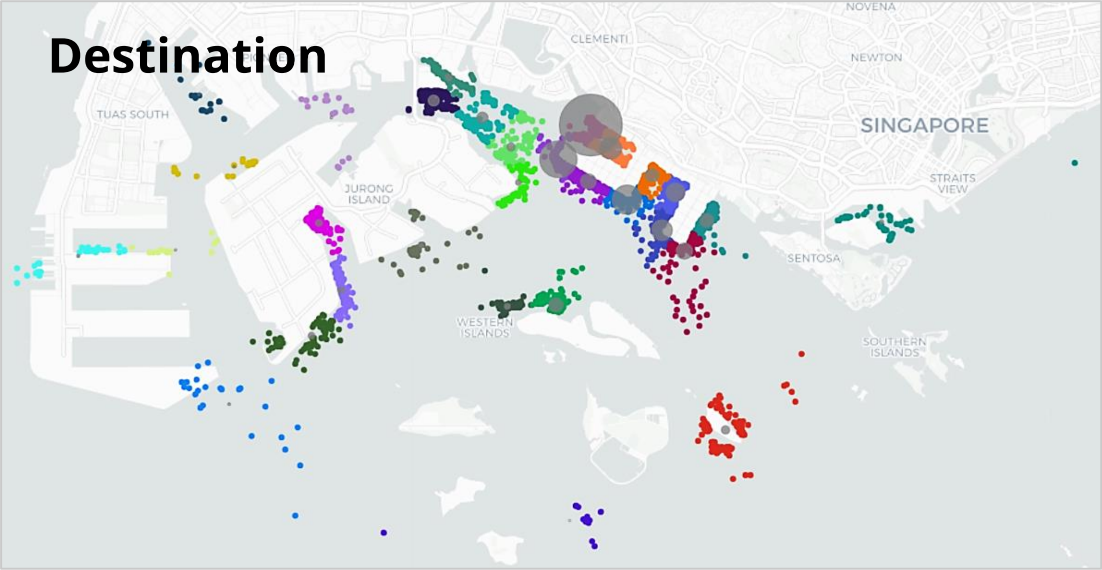
Engine working mechanism

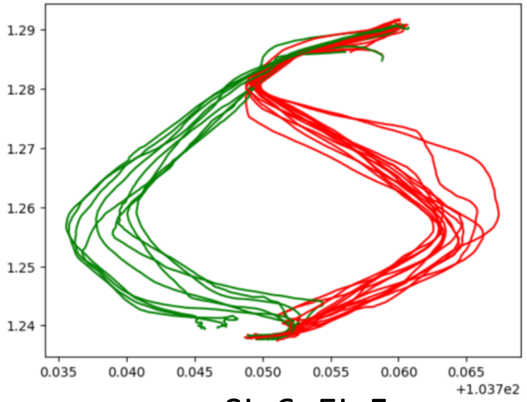
Analytics to assure data "semantically" correctness:

1. Cross-check with domain commonsense, physical law, principle and mechanism;
2. Cross-evaluate data from different sources for insight consistency (or identify data issues);
3. Only verified data of quality is further processed/AI modelling ready.

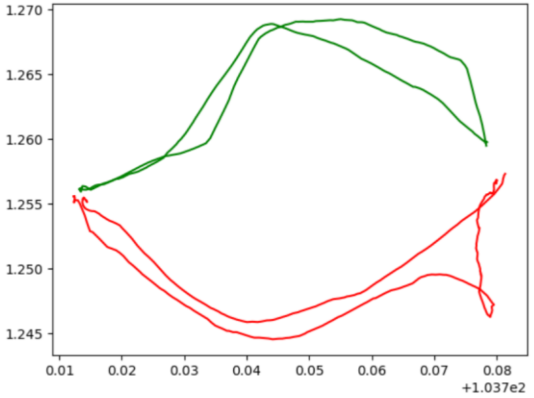
Harbor Tug Transit Pattern Extraction



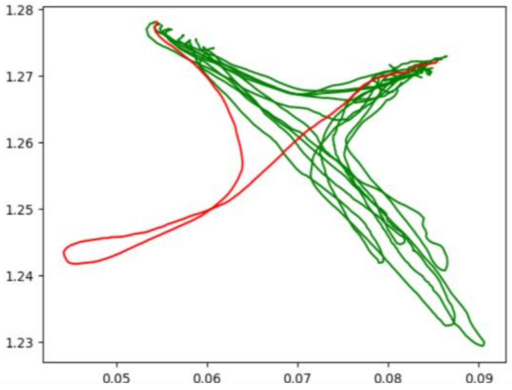




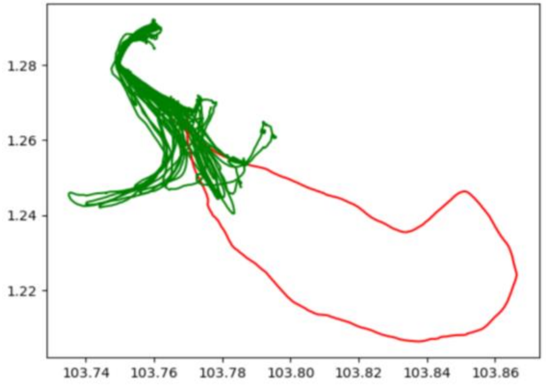
SL-6_EL-5



SL-22_EL-8



SL-1_EL-12

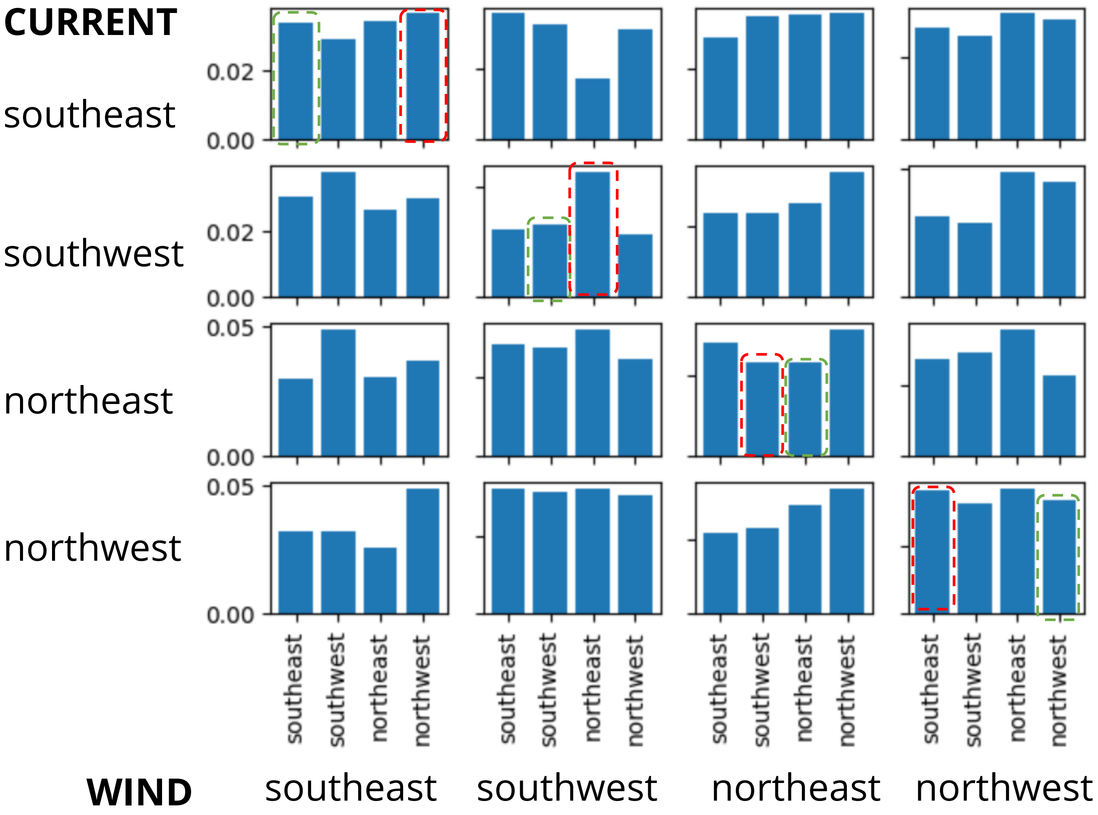


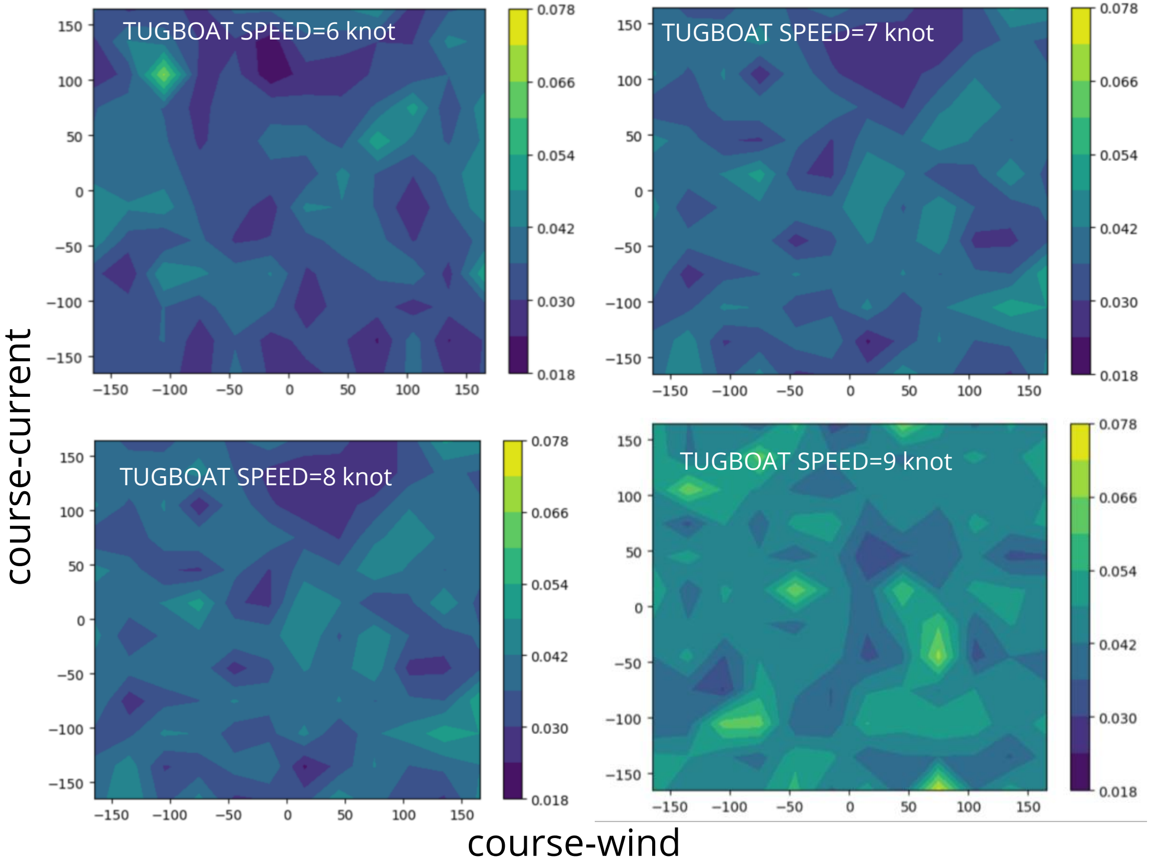
SL-7_EL-1

Environmental Factor analytics the impact on fuel consumption

Environment data: ERA5 hourly data on single levels from 1959 to present (u, v vector)

Study on relative angular relationship of tugboat, wind and current direction





TUGBOAT SPEED=7 knot, Vessel course and heading angle less than 5 degree (a. excluding the turning impact; b. has large wind/current magnitude in/towards follow/against direction for more obvious impact illustration)

Speed is the most significant factor, in general can observe that following wind/current will consume less fuel

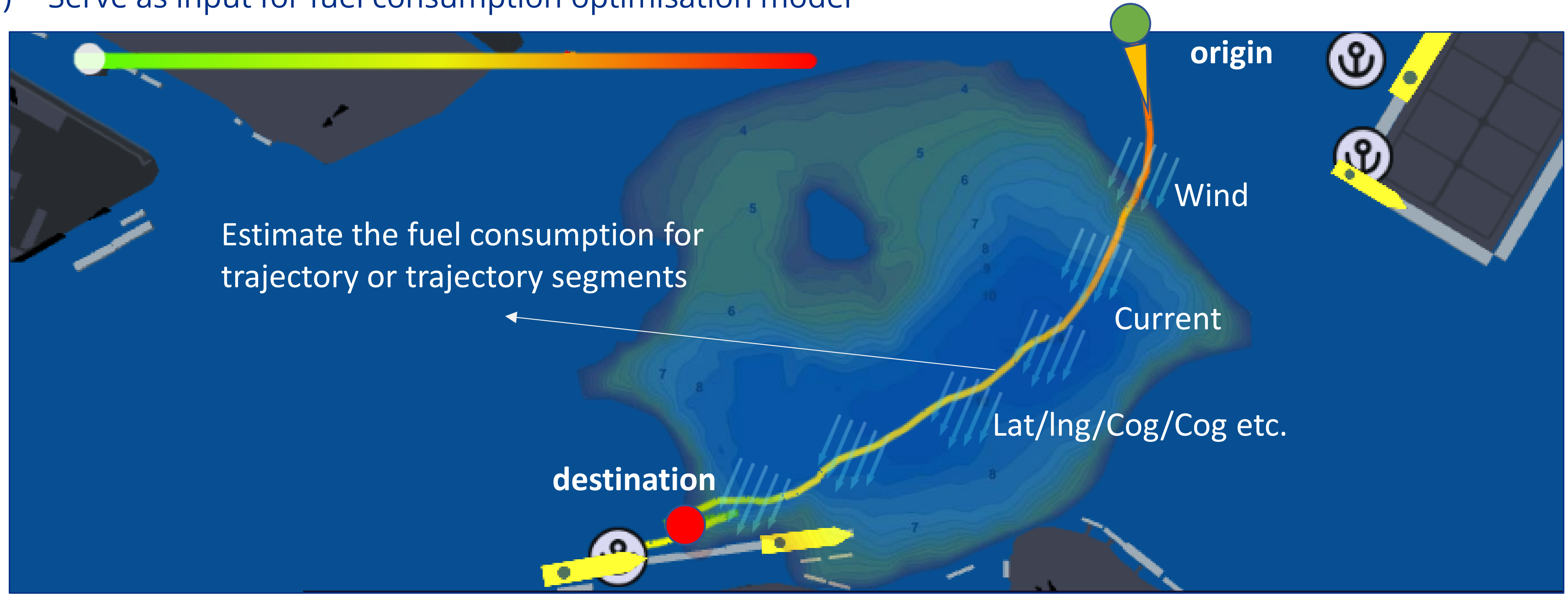
Harbor Tug Transit Fuel Consumption Estimation

Based on the navigating and environmental factors (speed, course, wind, current etc. sequence) for fuel consumption estimation/prediction

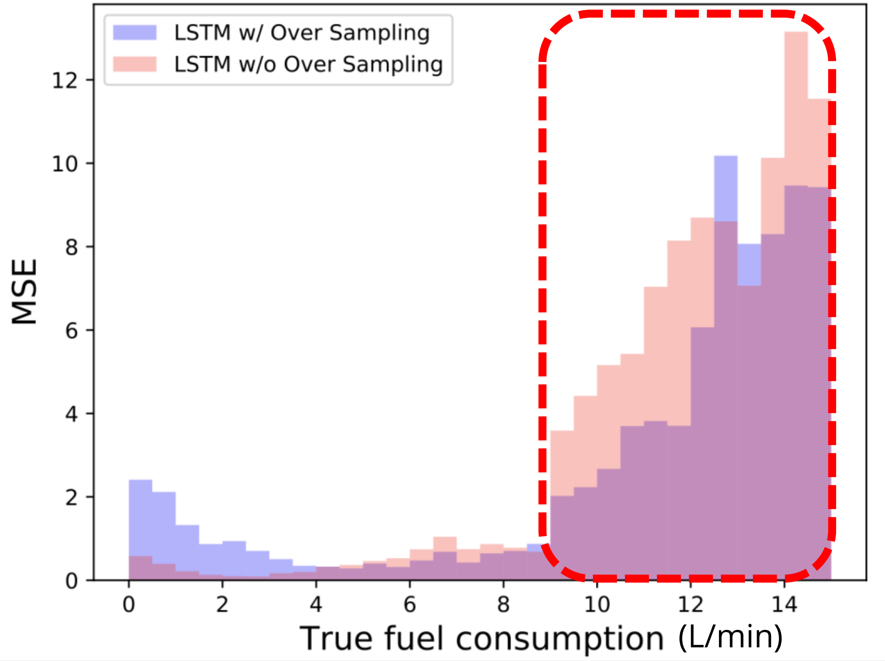
The fuel consumption prediction(FCP) functionalities support the followings:

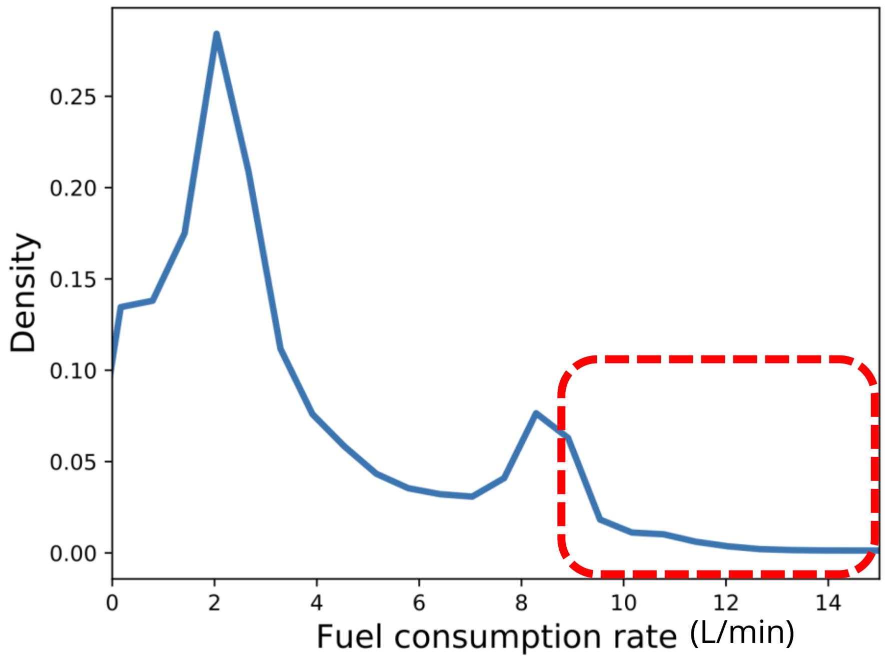
i) Learning based method (AI model) for fuel consumption estimation (capture latent relation between fuel consumption and all the potential factors)

ii) Serve as input for fuel consumption optimisation model



Harbor Tug Transit Fuel Consumption Estimation





LSTM performs worse on scarce data (Error is negative correlated with data density), even with the assistance of resampling.

Use MLP to avoid overfitting and deal with scarce data, which leads to an ensemble model

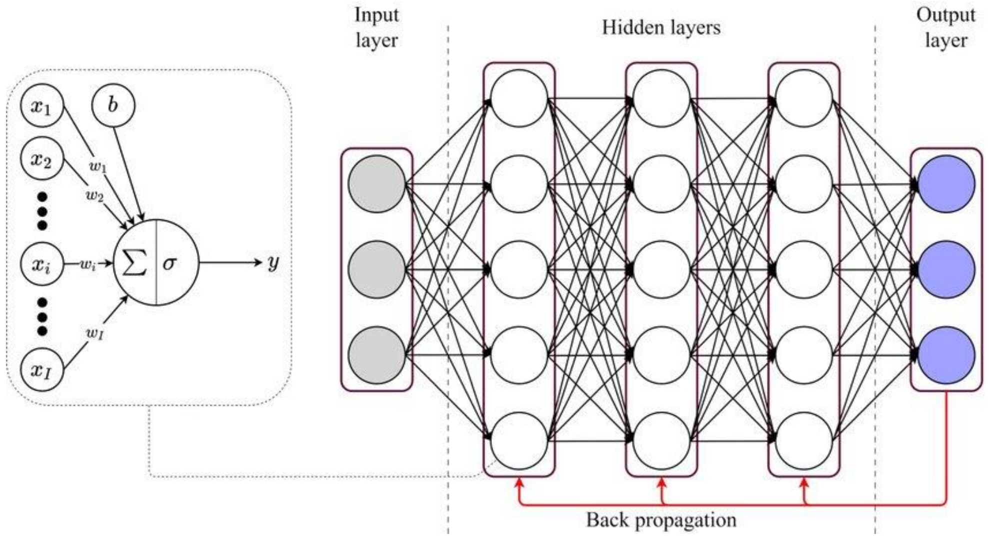
$$\hat{y}_t = \begin{cases} \mathrm{MLP}(x_t), & \text{if } \mathrm{MLP}(x_t) > 9 \\ \mathrm{LSTM}(x_{(t-w):t}), & \text{otherwise.} \end{cases}$$

Harbor Tug Transit Fuel Consumption Estimation

Based on the navigating and environmental factors (speed, course, wind, current etc. sequence) for fuel consumption estimation/prediction

More details about the model:

- The extracted training data is length-variable trajectories for a single tugboat
- Predict fuel consumption rate based on environment factors and operator parameters (total 13 features)
- Innovate proposing an ensemble model to deal with such data distribution (solve challenges on the scarce data in high fuel consumption range)



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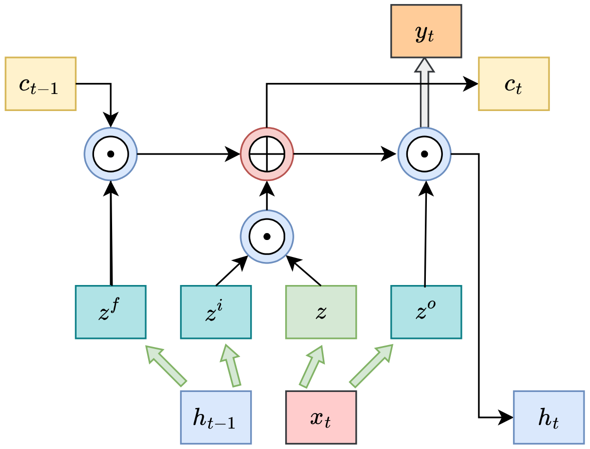


$$\mathcal{L}_{\text{LSTM}} = \prod_{j=1}^{J} \prod_{t=w}^{|Tr_j|} p(y_t|x_t, ..., x_{t-w})$$

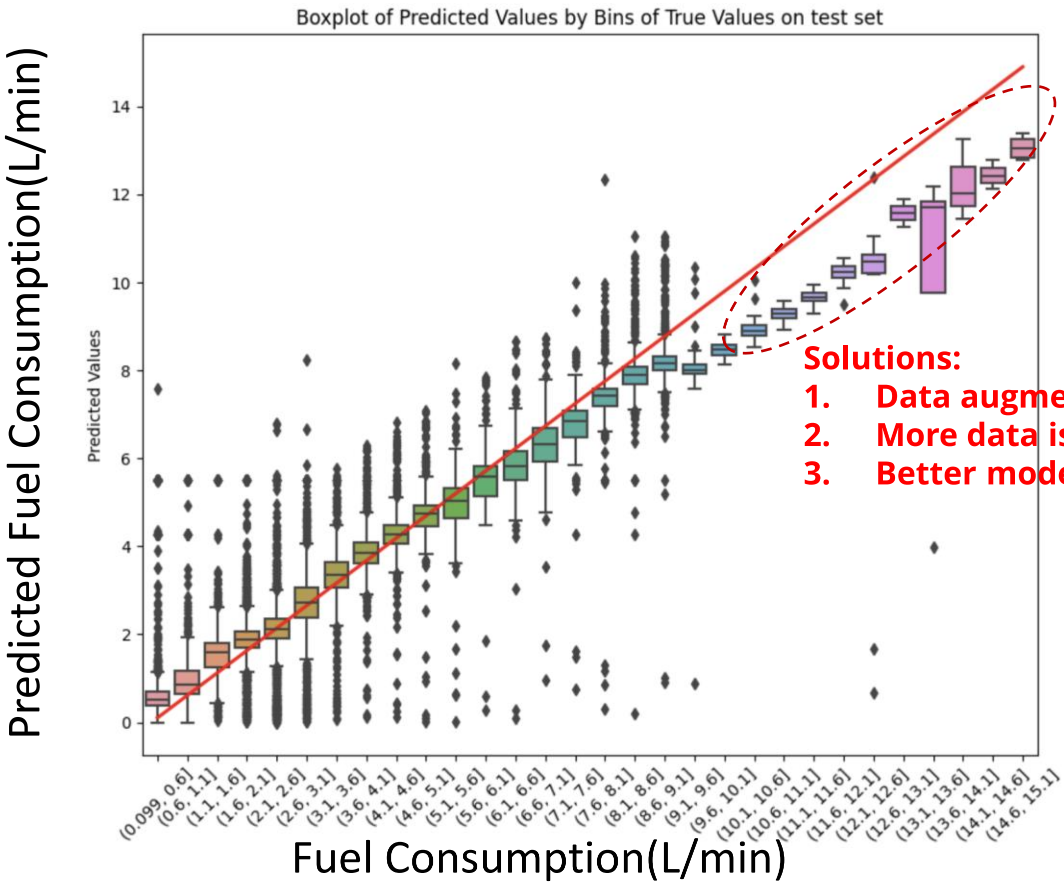
$$c_t = z^f \odot c_{t-1} + z^i \odot z$$
$$h_t = z^o \odot tanh(c_t)$$
$$\hat{y}_t = \sigma(W h_t),$$

MLP for high fuel consumption rate range

LSTM for low fuel consumption rate range

Harbor Tug Transit Fuel Consumption Estimation

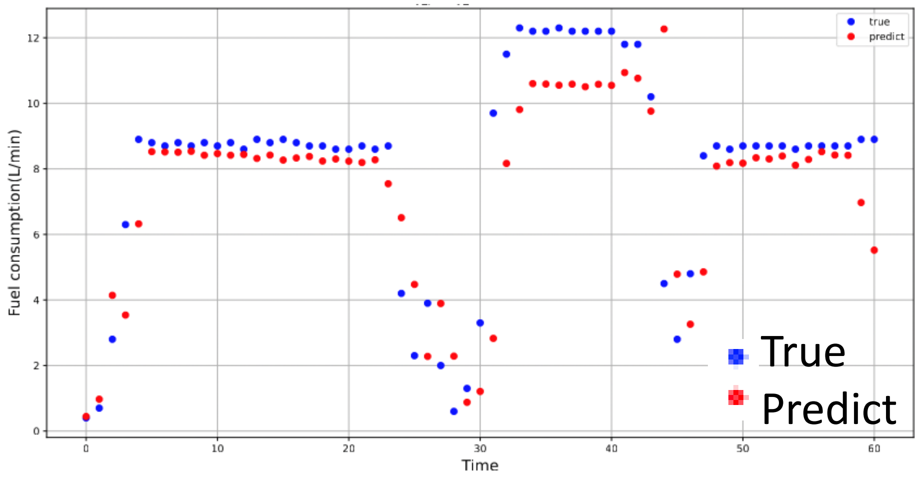
Testing & evaluation performance:



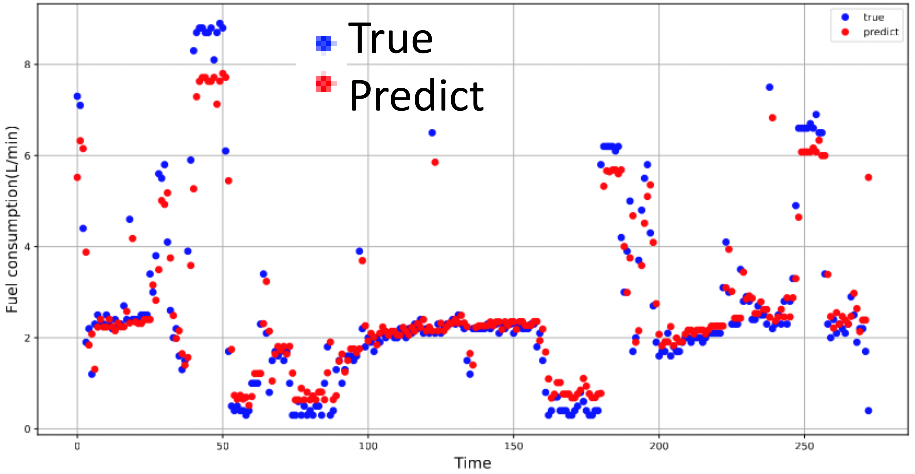
Solutions:

1. **Data augmentation**
2. **More data is required**
3. **Better model**

Overall test performance



Example 1: Trajectory 1320



Example 2: Trajectory 1507

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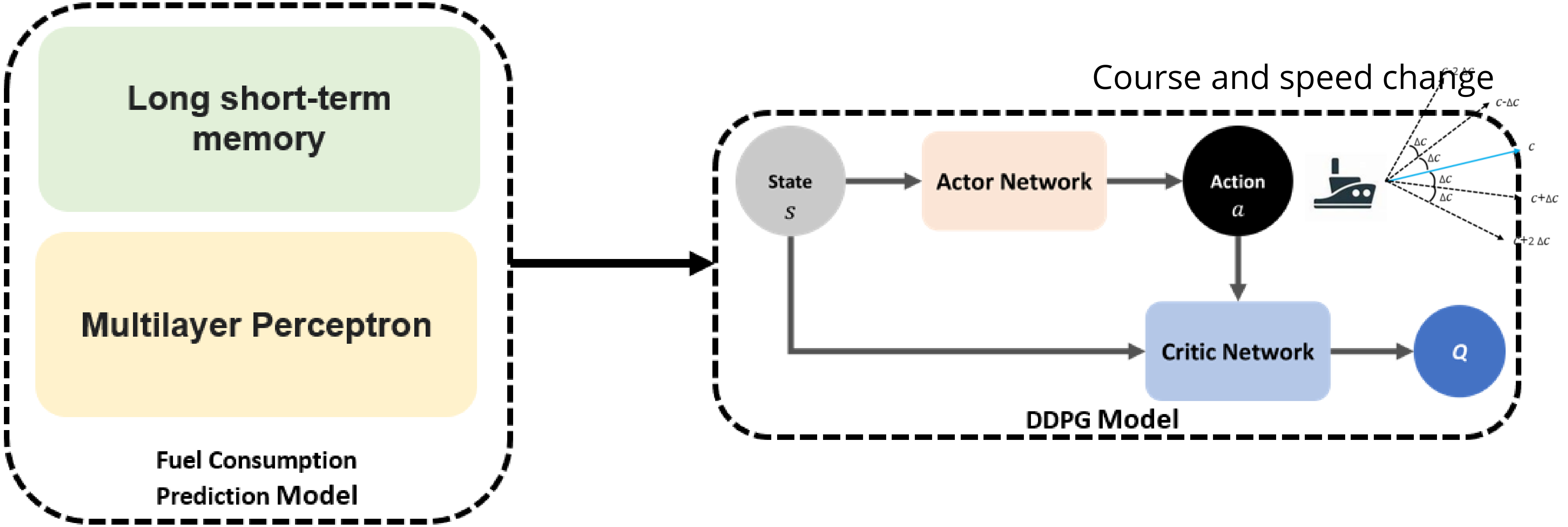
Harbor Tug transit Fuel Consumption Optimization

I. Quantify the reward function
II. Training the network to reduce fuel consumption



Fuel Consumption Prediction(FCP) model

RL based transit route generation for fuel consumption optimisation

Harbor tug transit fuel consumption optimization

Historical transit instance by human ship master

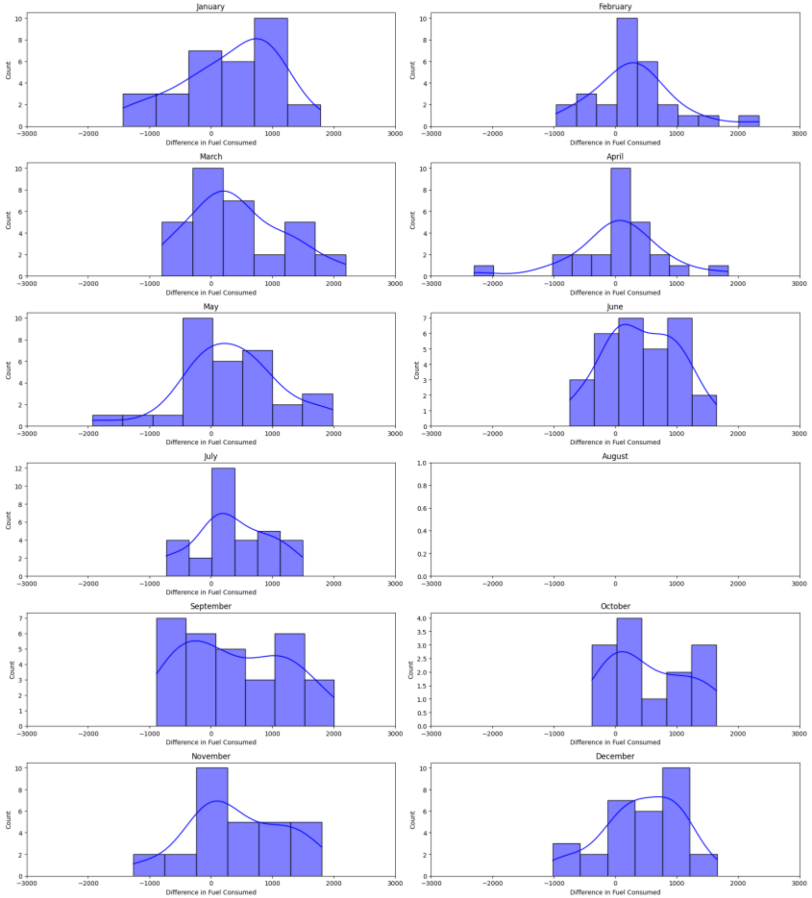
An observable deviation occurs as the tugboat follows a curved path on its way to the terminal.

Transit generated by our algorithm

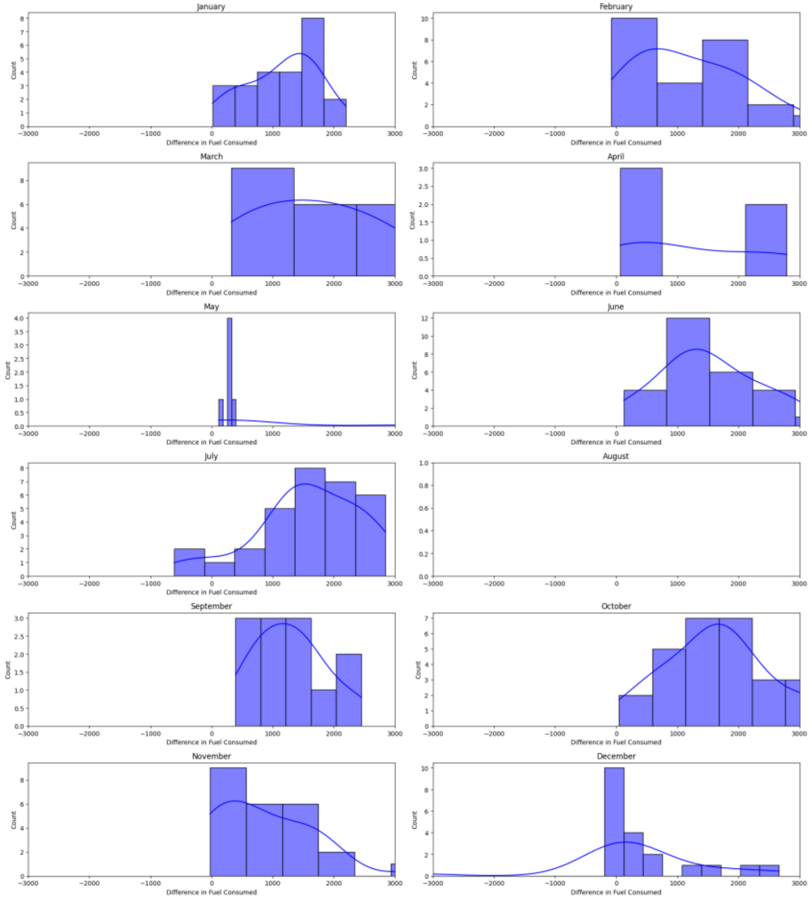
the model recommends a more direct and efficient route.

Establish classifier to detect sensor issue

Capella



Oak



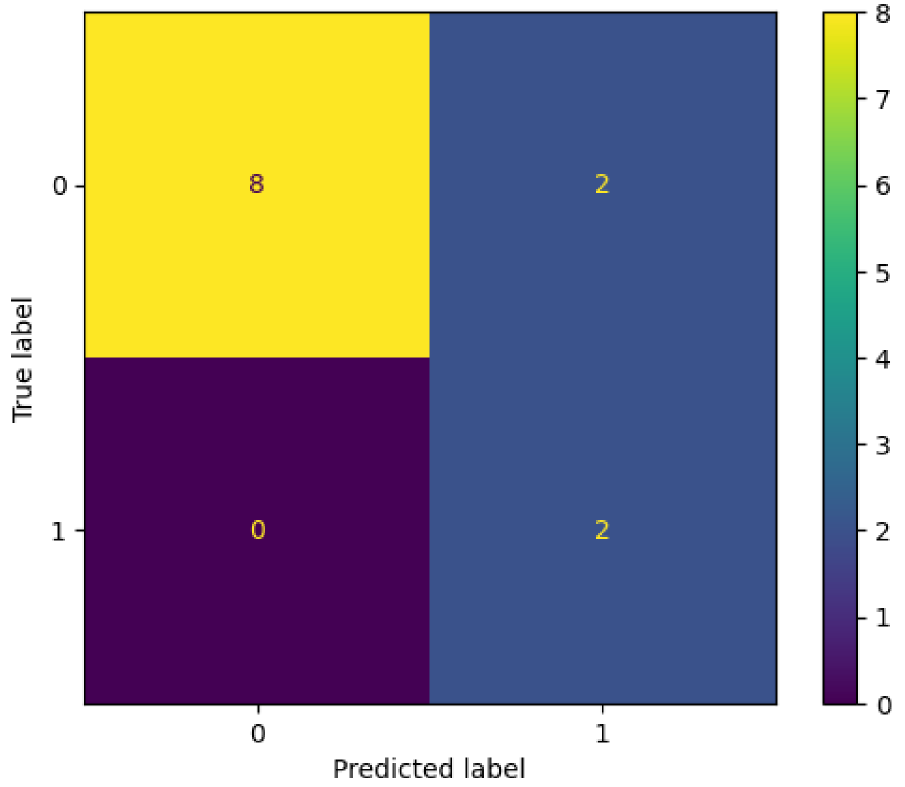
Normal

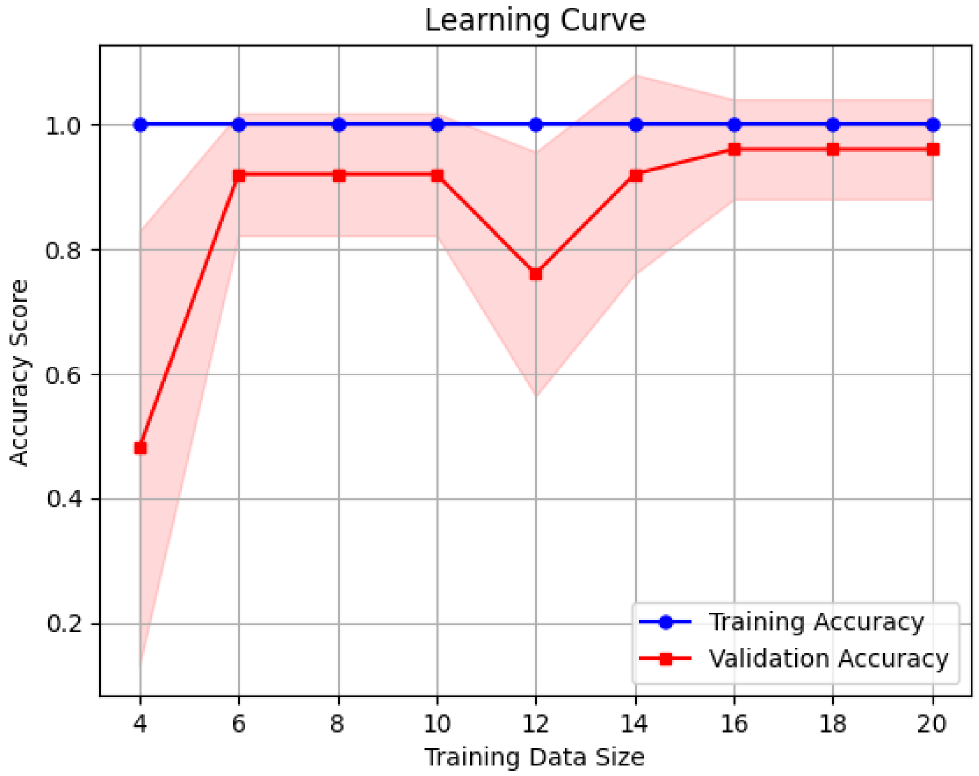
Abnormal

Comparing the difference distribution in daily consumption from sounding record and fuel flow meter to build the classifier

Establish classifier to detect sensor issue

	Conditional Labelling	SVM Model
Accuracy Score	100%	83%





Two models, Conditional Labelling and SVM, are developed for testing and evaluation

Toolkits With The Technologies Developed

1

Daily tug operation state extraction

1) Daily extraction for all the tugs
2) Select a tug for visualizing its operation sequence Overlay with fuel consumption insights

2

Data/sensor anomality identification

1) Identify the potential sensor/data issue
2) Reason categories, e.g., statistics of daily difference and distribution for past one month

3

Transit route planning and optimization

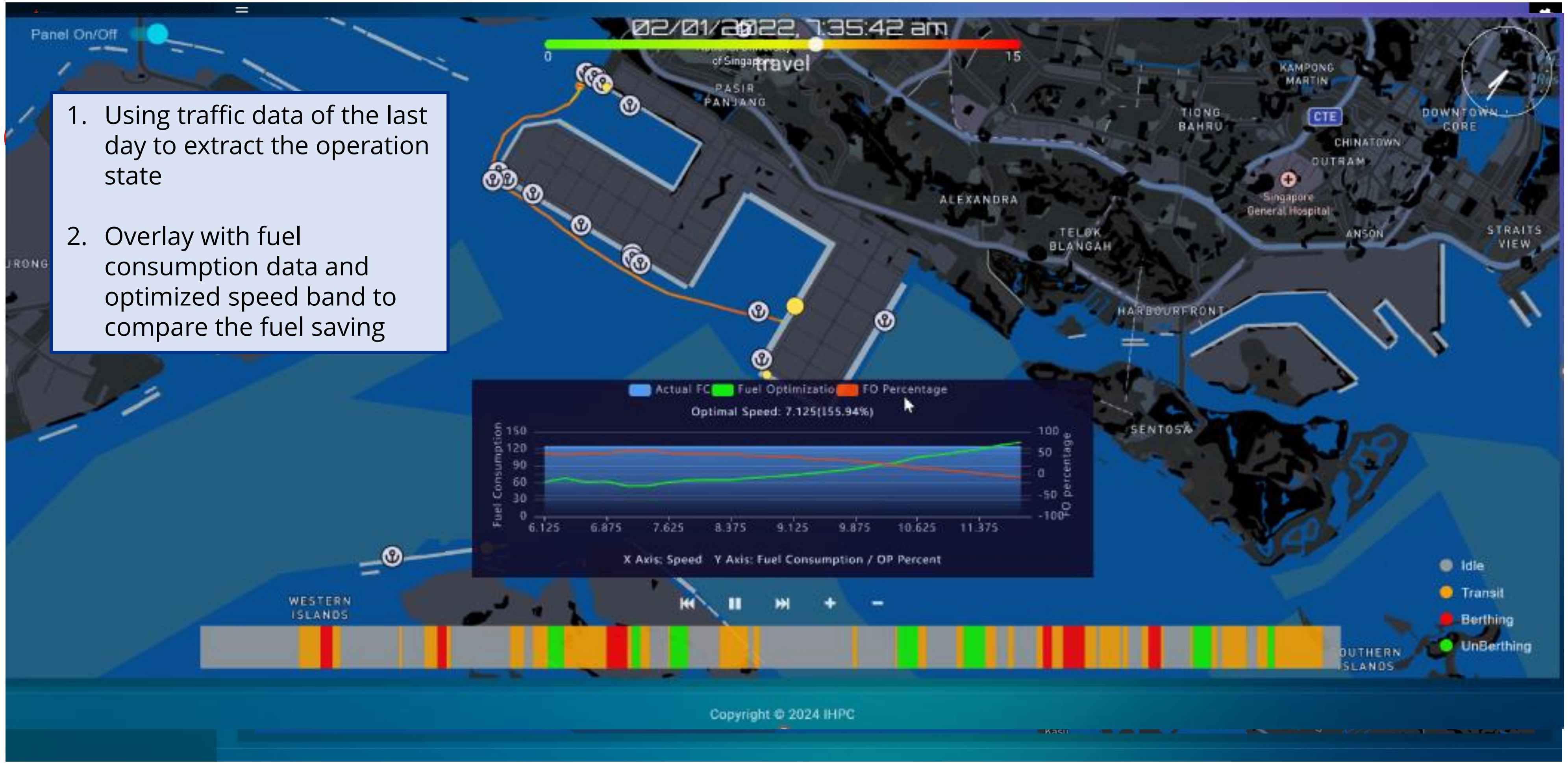
1) Decision support and recommendation on the most fuel saving route
2) Decision support and recommendation the speed pattern along the route

Toolkits With The Technologies Developed

Tool 1

Tug operation state review with fuel consumption insights

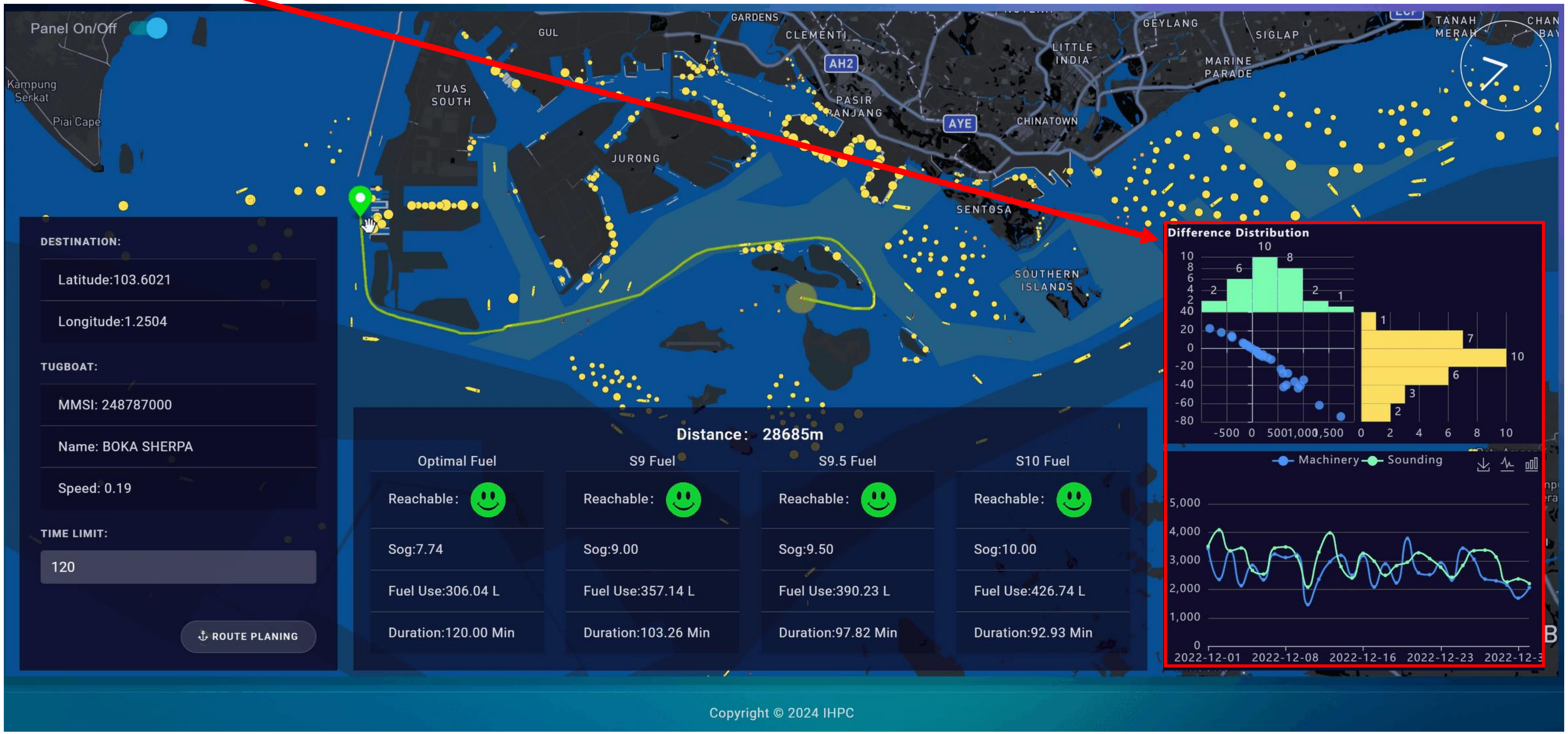
1. Using traffic data of the last day to extract the operation state
2. Overlay with fuel consumption data and optimized speed band to compare the fuel saving



Toolkits With The Technologies Developed

Tool 2 Data/sensor issue identification & alert

Tool 3 Transit route planning and optimization



Summary & future exploration

➢ **Domain data have great potential for maritime decarbonization**
- Energy/fuel/emission insight generation
- Energy/fuel/emission pattern and knowledge mining
- Prerequisite for AI modeling

➢ **AI models empower better energy use, fuel saving and sustainable goal**
- Track, monitor and impact
- Decision support to decarbonisation strategies
- Support infrastructure building
- Energy consumption and emission model optimisation
- Weather routing for wind propulsion
- and so on ……

Thanks for your attention!