

PREDICTIVE MONITORING SYSTEM FOR COAL DELIVERY VESSEL

Group 2 :

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OVERVIEW

01 Background and Project Objectives

02 Unified Modeling Language (UML)

03 Features & Deliverables

04 Timeline, PIC & Mockups

05 Reference

ZALECHA BARUNA



01 Background and Objectives

Company Context

PT Bahtera Adhiguna (BAG) is a subsidiary of PT PLN (Persero) managing coal & energy transport for PLN and its partners.

Key Challenge

Fuel accounts for up to 40% of BAG's operational cost across 16 vessels using mixed manual/digital systems.

Project Goal

Deploy an on-premise Fuel Monitoring System (FMS) for Zalecha Baruna & Kencana Baruna to enhance capacity, accuracy, and efficiency.

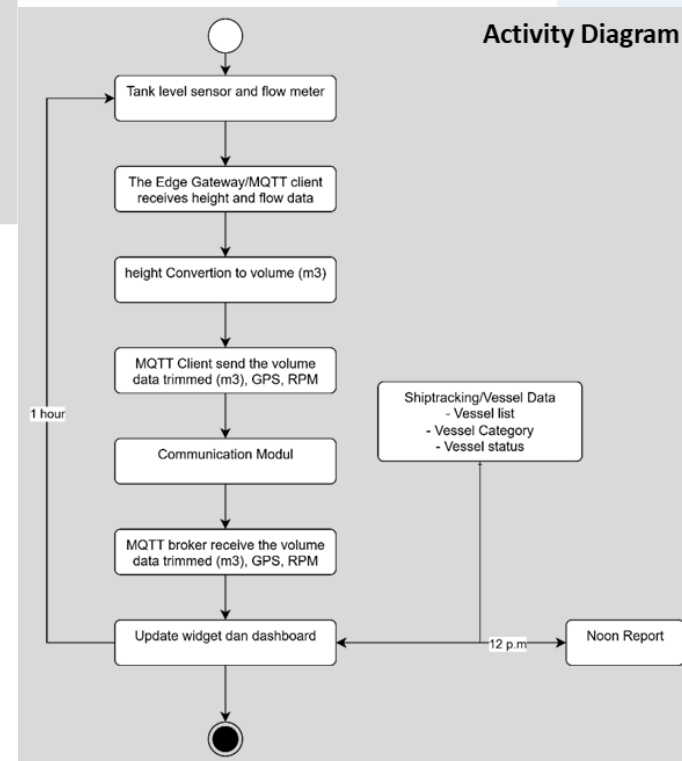
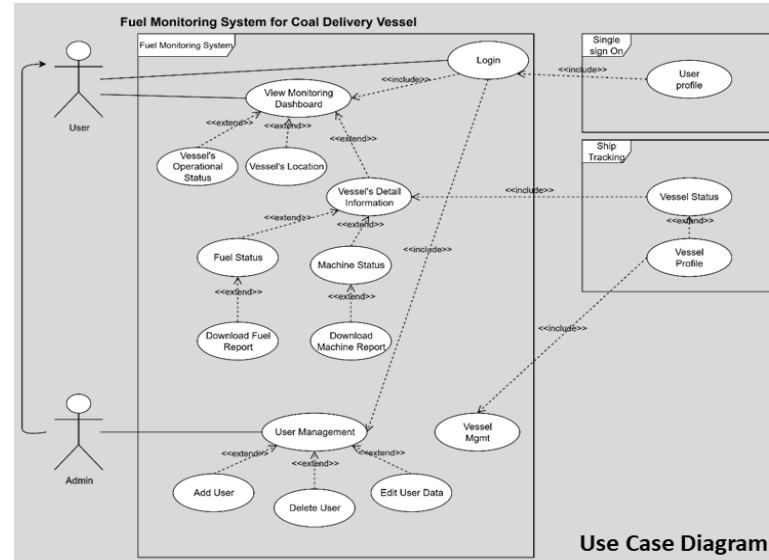
Objectives

- 1 Automatic measurement of fuel inventory in each tank.
- 2 Automatic measurement of fuel consumption for Auxiliary and Main Engines.
- 3 Integration of manual readings into centralized FMS dashboard.
- 4 Predictive fuel consumption and Estimated Time of Arrival (ETA).

02 UNIFIED MODELING LANGUAGE (UML)

To achieve the goal of this project, the primary objectives of this project are follows :

1. Design a real-time fuel monitoring system for bulk carrier by integrating flowmeter sensors, tank level gauges, and engine operational data.
2. Develop reliable MQTT-based communication framework (publisher, broker, subscriber) that enables efficient, lightweight, and secure data transmission between shipboard sensors, edge gateway, and monitoring dashboards.
3. Create visualization and analytics tools such as dashboards, trend charts, key performance indicators for real-time analysis and evaluation of fuel consumption and efficiency.
4. As a basis for operational decision making by providing accurate and real-time fuel usage information, identifying abnormal consumption patterns, and supporting trip optimization.
5. Ensure the fuel monitoring system can be used on other vessels, is integrated with cloud platforms, and is aligned with international standards on energy efficiency (e.g. IMO EEOI).
6. To develop data for **Predictive fuel consumption and predictive time arrival**



03 FEATURES & DELIVERABLES (1/4)

Ship Configuration System

Connects the central system with real-time data from each vessel, including fuel sensors and tank capacity information. Ensures every vessel has a unique configuration for more accurate and consistent fuel measurement.

Central Application System

The main platform used by operators to monitor vessels. Displays ship status, location, fuel level, and consumption history in an interactive dashboard. Designed to be user-friendly for NOC operators, fleet managers, and auditors.

Analytics & Visualization

Provides visual and analytical insights into fuel consumption patterns, vessel performance, and estimated speed and arrival time. Equipped with port and route maps, and a dark mode interface for improved usability in control room environments.

03 FEATURES & DELIVERABLES (2/4)

Must Have

Auth & RBAC – Role-based read-only

UI Frame – UI Kit

Fleet Map & Status – Clustering, filters

Vessel Dashboard – Tank cards

Trends & History – 24h/7d charts

Alert Center – View-only

Export – CSV/PDF snapshot

UI/Performance – Auto-refresh + loaders

Should Have

Calibration Viewer – Curve overlay

Geofence – Port/Route overlay

Analytics Widgets – Top-N vessels

Analytics – Speed Prediction (read-only)

Could Have

Dark Mode / PWA (optional)

03 FEATURES & DELIVERABLES (3/4)

IoT Edge Gateway



Level Radar Sensor



Marine Inertial
Measurement Unit

Edge Gateway Computing

Payload → Central System (Agreement)

TrimCalc – Calculate Volume by Ship Trim

VolCalc – Level Sensor → Volume Curve

AssetTank & AssetSensor – IDs & Info

03 FEATURES & DELIVERABLES (4/4)

Deliverables Summary



Design System

- Wireframes & Mockups
- Lightweight Design System



Testing

- UI & E2E Test Plan



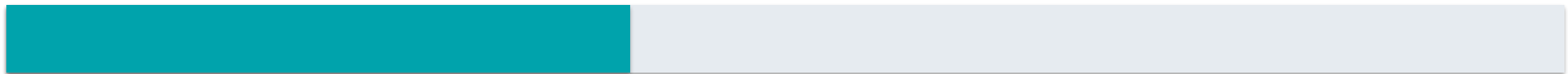
Data/Model

- View/Data Model
- Calibration Curve Overlay (viewer)

04 TIMELINE, PIC & MOCKUP (1/4)

Estimated Start Month: September 2025

Current Progress:  **Report Design (Sprint 5) — Analysis & Design Phase Completed**



Business Modelling

Sprint 1–2

Define business case, scope, and baseline workflow.

Requirements & Design

Sprint 2–5

Document requirements and design prototypes.

Development

Sprint 5–9

Build central app modules: Fleet Map, Dashboard, Alerts, Reports.

Testing & Deployment

Sprint 9–10

UAT, data migration, and final go-live.

04 TIMELINE, PIC & MOCKUP (2/4)

Business & Requirements (Sprint 1–4) –  Done

Analysis & Design (Sprint 4–5) –  Done (Report Design completed)

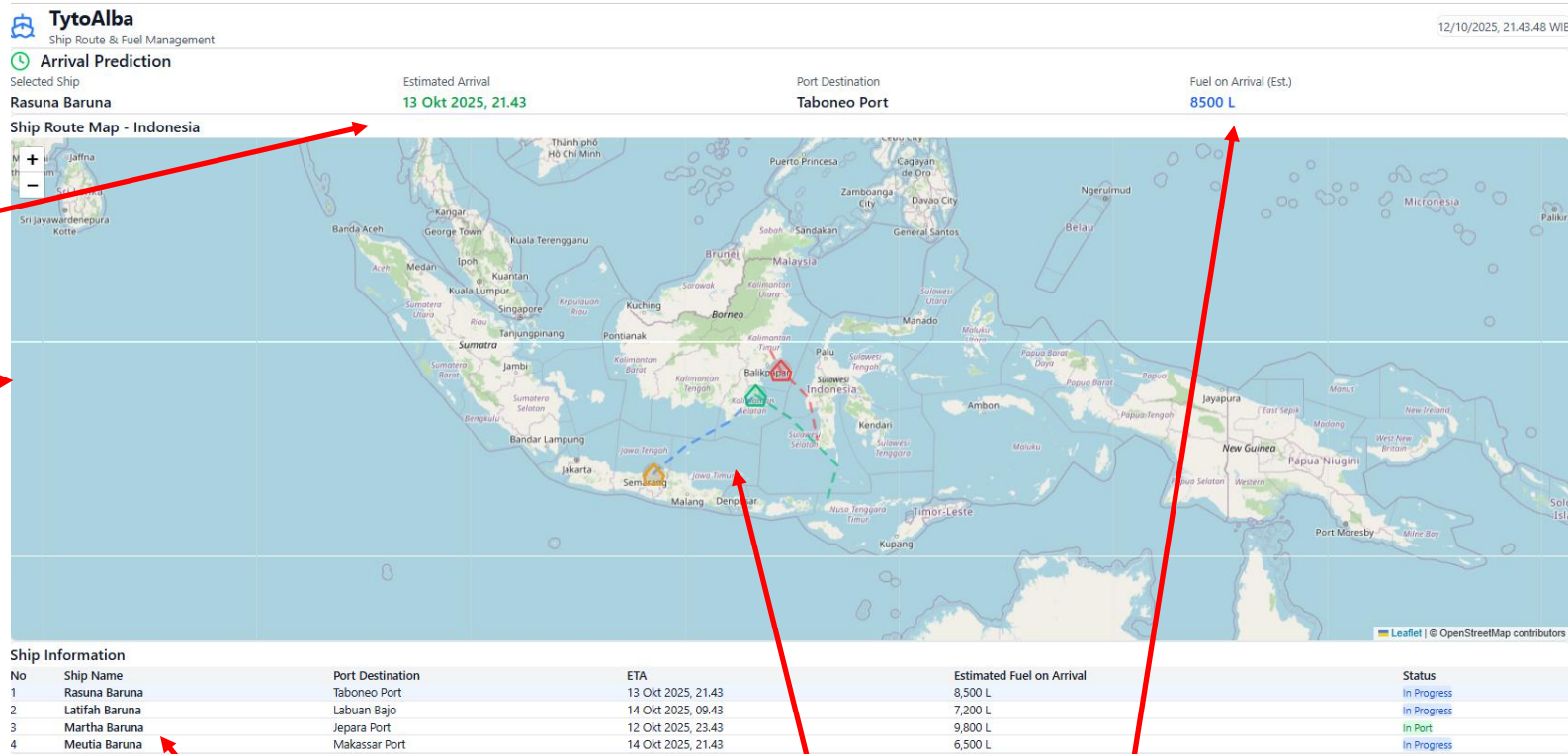
Development (Sprint 6–9) –  Ongoing (UI Kit, Fleet Map, Dashboard)

Testing & Deployment (Sprint 9–10) –  Pending

Next Milestones:

- Start UI Kit & Fleet Map Development (Sprint 6)
- Begin API Integration setup
- Prepare UAT Environment (Sprint 9)
- Target Go-Live: **Februari 2026**

04



Estimated Arrival

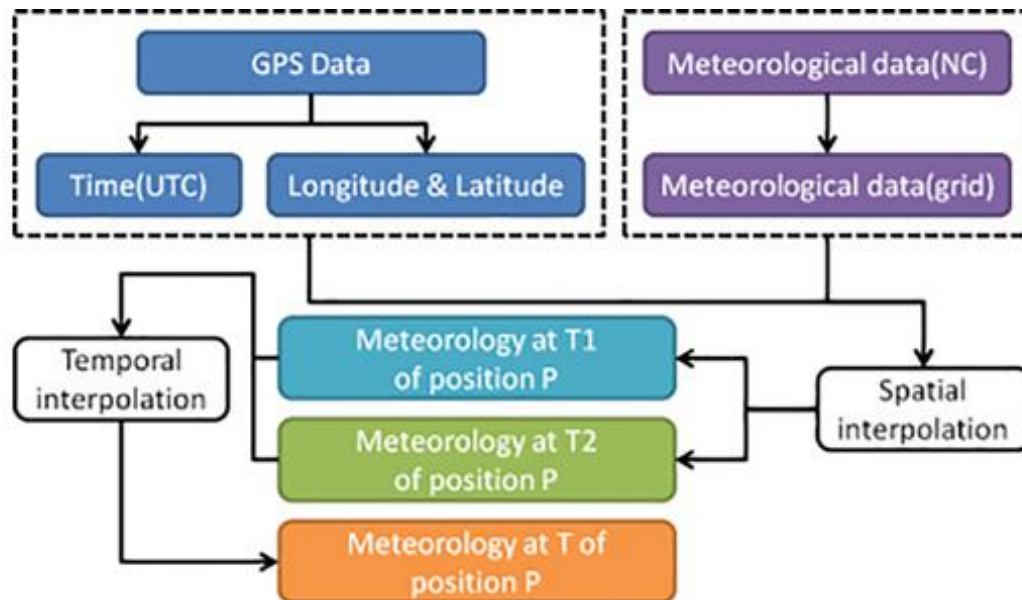
Indonesia Bounding
Box

UI Auto Refresh.
Click on row to focus

Ship Route

Estimate Fuel on Arrival

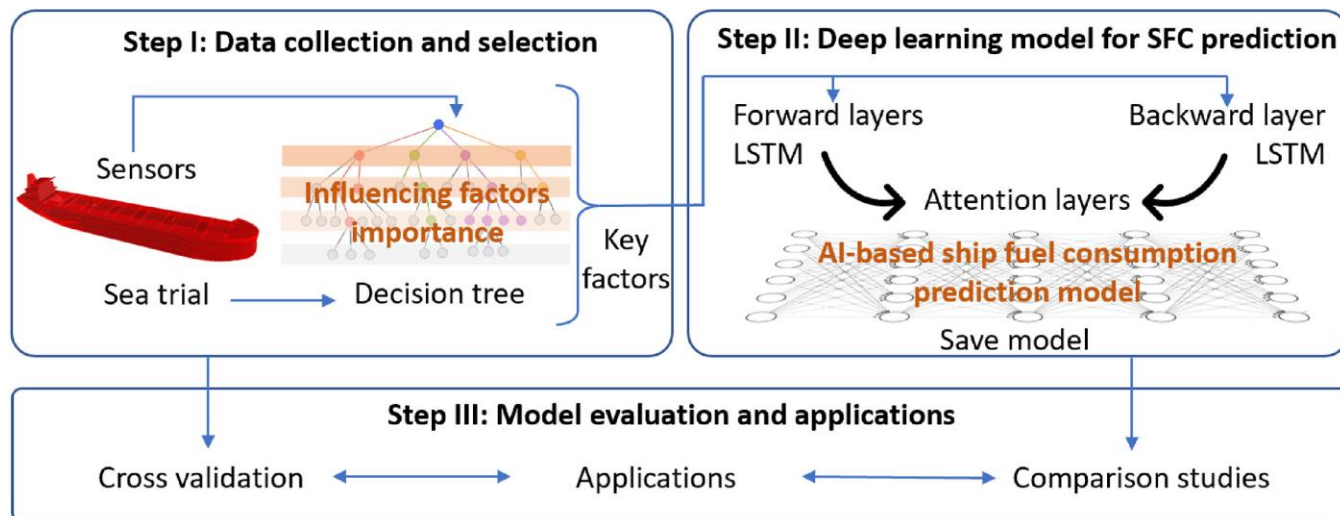
Research on Ship Main Engine Fuel Consumption Model With Data Integration and Noise Cleaning



Integrate meteorological data into ship operational data, taking into account temporal and spatial variations, to enhance the dimensionality of the operational data and improve the quality of models for predicting fuel consumption in vessels

Zhang, M., Tsoulakos, N., Kujala, P., & Hirdaris, S. (2024). A deep learning method for the prediction of ship fuel consumption in real operational conditions. *Engineering Applications of Artificial Intelligence*, 130(December 2023), 107425.
<https://doi.org/10.1016/j.engappai.2023.107425>

A deep learning method for the prediction of ship fuel consumption in real operational conditions

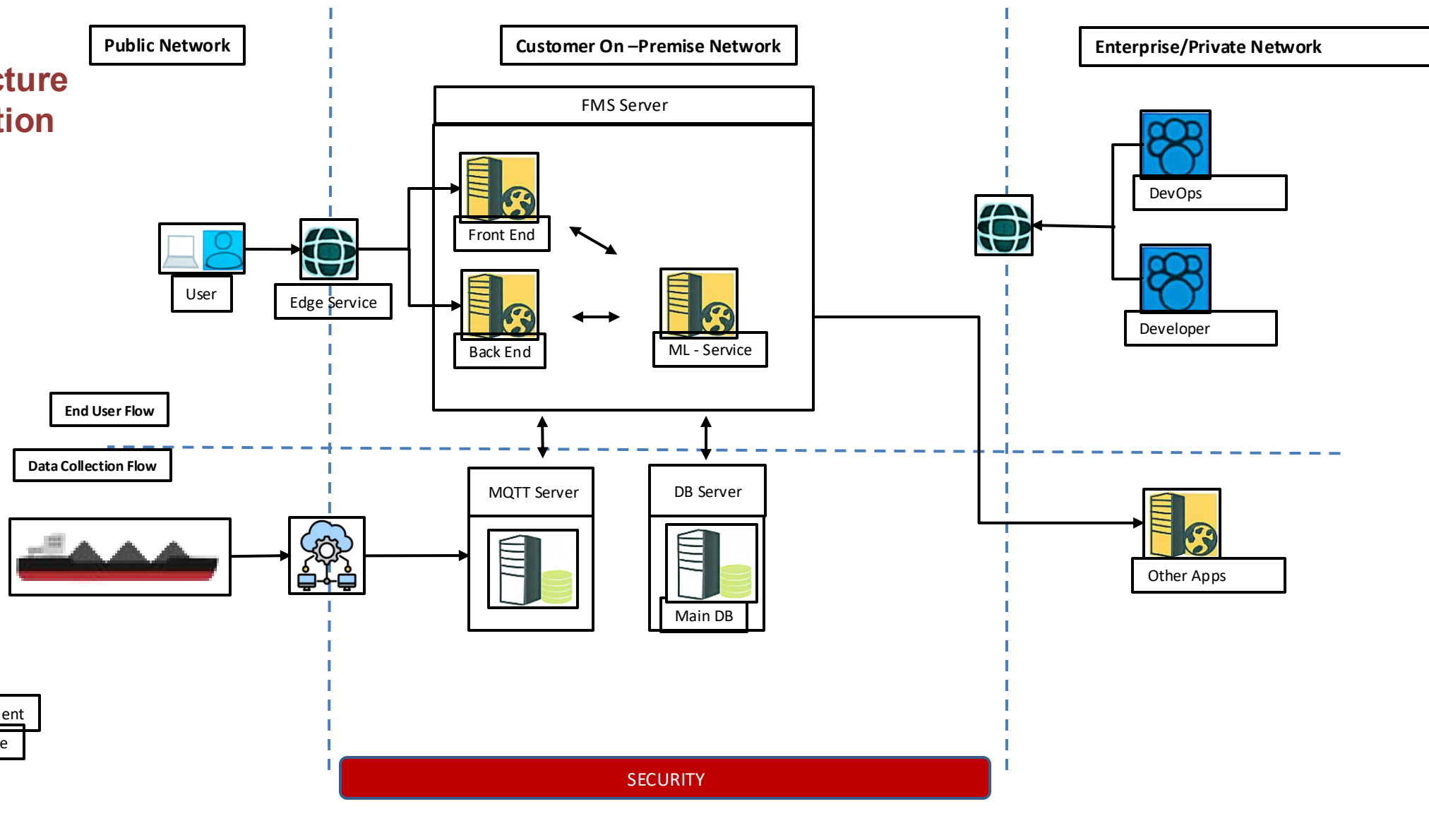


In this paper, a decision tree (DT) is used to evaluate the importance of factors encompassed on extensive big data analytics records and consequently select key influencing factors with impact on SFC.

A Bi-LSTM (Bidirectional Long Short Term Memory) with attention mechanism method is employed. The methodology presented comprises of the following three steps :

1. Data collection and the importance evaluation of influencing factors
2. A DLM for the prediction of ship fuel consumption.
3. Cross validation, comparison, and applications

Our Architecture Recomendation



TytoAlba

-Backend
-Database
-docker
-frontend
--public
--src

-ml-service

--train-arrival-model.py

--train-fuel-model.py

--train-arrival-model.py

Train model

```
print("\n 🛠 Training Random Forest model...")
predictor = ArrivalPredictor()
predictor.train(X_train, y_train)
```

Evaluate model

```
print("\n 📊 Evaluating model...")
y_pred_train = predictor.predict(X_train)
y_pred_test = predictor.predict(X_test)
```

Calculate metrics

```
train_mae = mean_absolute_error(y_train, y_pred_train)
train_rmse = np.sqrt(mean_squared_error(y_train, y_pred_train))
train_r2 = r2_score(y_train, y_pred_train)
```

```
test_mae = mean_absolute_error(y_test, y_pred_test)
test_rmse = np.sqrt(mean_squared_error(y_test, y_pred_test))
test_r2 = r2_score(y_test, y_pred_test)
```

--train-fuel-model.py

Train model

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print("\n 🛠 Training Random Forest model...")
predictor = FuelPredictor()
predictor.train(X_train, y_train)
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Evaluate model

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```

1. Abdi, A., & Amrit, C. (2024). Enhancing vessel arrival time prediction: A fusion-based deep learning approach. *Expert Systems with Applications*, 252(PA), 123988. <https://doi.org/10.1016/j.eswa.2024.123988>
2. Zhang, M., Tsoulakos, N., Kujala, P., & Hirdaris, S. (2024). A deep learning method for the prediction of ship fuel consumption in real operational conditions. *Engineering Applications of Artificial Intelligence*, 130(December 2023), 107425. <https://doi.org/10.1016/j.engappai.2023.107425>
3. Chen, Y., Huang, Z., & Feng, L. (2024). Research on Ship Main Engine Fuel Consumption Model With Data Integration and Noise Cleaning. *IEEE Access*, 12(October), 154546–154569. <https://doi.org/10.1109/ACCESS.2024.3478783>
4. Kim, S.; Kim, H.; Jeon, H. Development of a Simplified Performance Monitoring System for Small and Medium Sized Ships. *J. Mar. Sci. Eng.* 2023, 11, 1734. <https://doi.org/10.3390/jmse11091734>

THANK YOU

