Berth Stay Prediction for Tanker Terminal

Introduction

Tanker shipping operation is a significant portion of maritime shipping. In 2020, the global oil tanker fleet had a capacity of around 601 million deadweight tonnages. Specific to Singapore, the global logistic networks mostly depend on tanker and air shipping. Figure 1 illustrates a brief transport description of the global logistic networks between tanker and air shipping and emphasises that tanker shipping is more heavily tilted and progressively increasing in the whole logistic landscape of Singapore.

Understanding and being able to forecast the upstream transport patterns and behaviours would enhance the efficiency of logistic networks. It is important for tasks, such as advanced pilot booking, advanced cargo operation scheduling, turnaround time saving, etc. Based on the Automatic Identification System (AIS) data and port operation data collected in the tanker terminal of Singapore, we investigate the problem of berth stay (or time to un-berth) prediction using a statistical learning approach, which refers to the following three innovative aspects:

(a) The data source is multi-faceted, such as operation data from terminal management and AIS;

(b) The process of berth stay is innovatively decomposed into multiple blocks;

(c) The cargoes are categorised based on their characteristics for individual modelling.

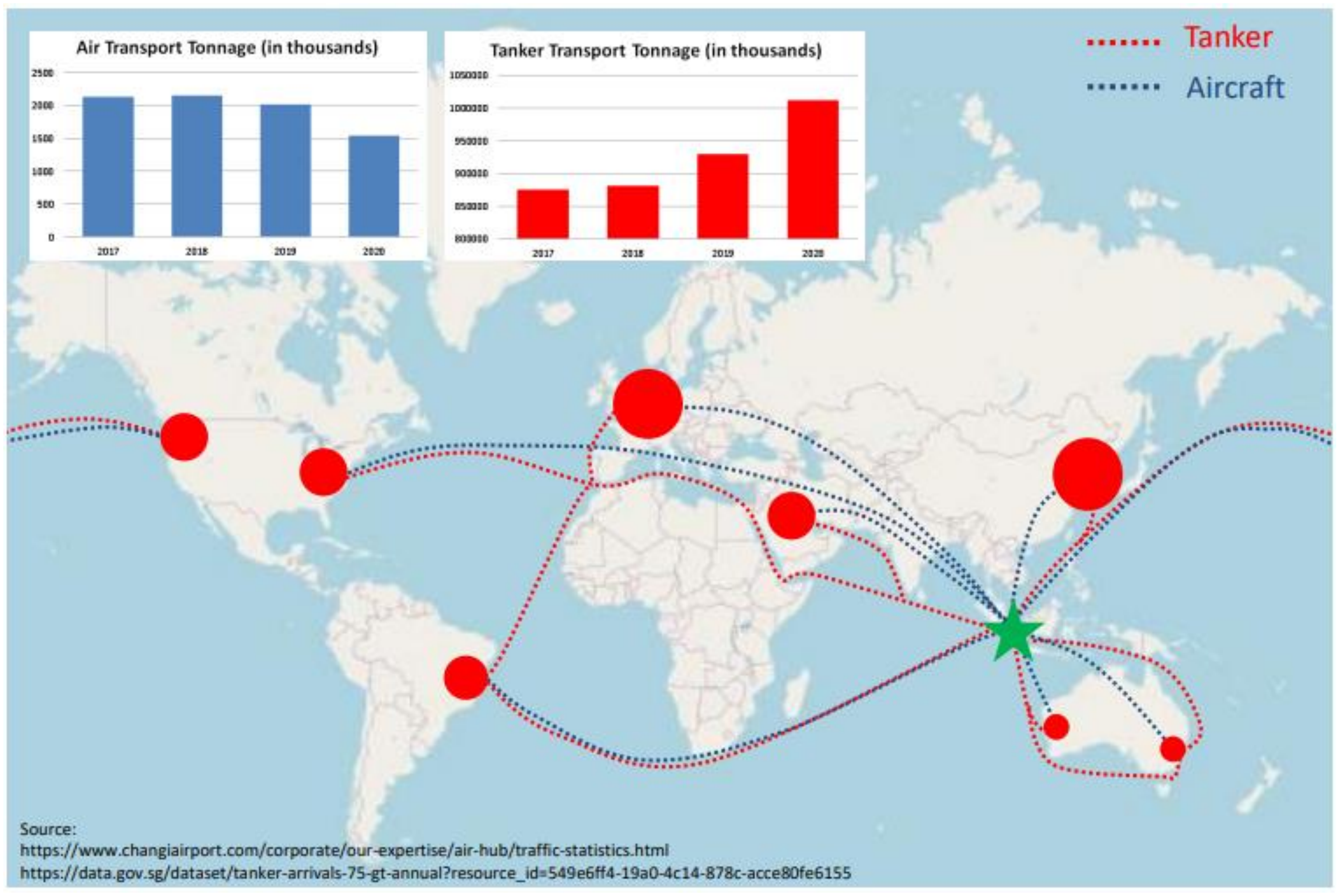

Figure 1. Global logistics to Singapore (tanker vs. air)

Standardisation of Key Port Events and Key Cargoes

We have standardised the key port operation events, including all fast, safety meeting, ullage before operation, cargo operation, Marpol prewash, stripping to shore, etc., to address potential misunderstandings caused by differing nomenclatures and terms used during port event processes across various terminals. A more detailed list of these standardised port operation events can be found in figures 2 and 3.

Due to the varying characteristics of different cargoes, we have categorised them into 8 distinct groups: Base Oil, OL, AL, AS, KOH, PIB1000, PIB2300 and PT. For further details on the specific attributes of each cargo type, please refer to Table 1.

Cargo Group	Cargo Name
G1	Base Oil (e.g., 600N, SN150, SN500, SN600, C600, EHC50, etc.)
G2	OL (e.g., OL200H, OL262, OL273, OL249SX, etc.)
G3	AL (e.g., AL305, AL305B)
G4	AS (e.g., AS305BD)
G5	KOH (e.g., KOH)
G6	PIB1000 (e.g., PIB1000)
G7	PIB2300 (e.g., PIB2300)
G8	PT (e.g., P.TERTRAMER)

Table 1. Key cargoes

Generic Workflow for Cargo Operation

Predicting berth stay is a more comprehensive process than predicting tanker cargo operations alone. While tanker cargo operations are a crucial part of berth stay, the latter encompasses the entire process from the vessel being anchored to departing the berth. Through data analysis, a generalised workflow for cargo operations has been identified, as shown in figures 2 and 3 for the discharging scenario and the loading scenario of tanker vessels respectively.

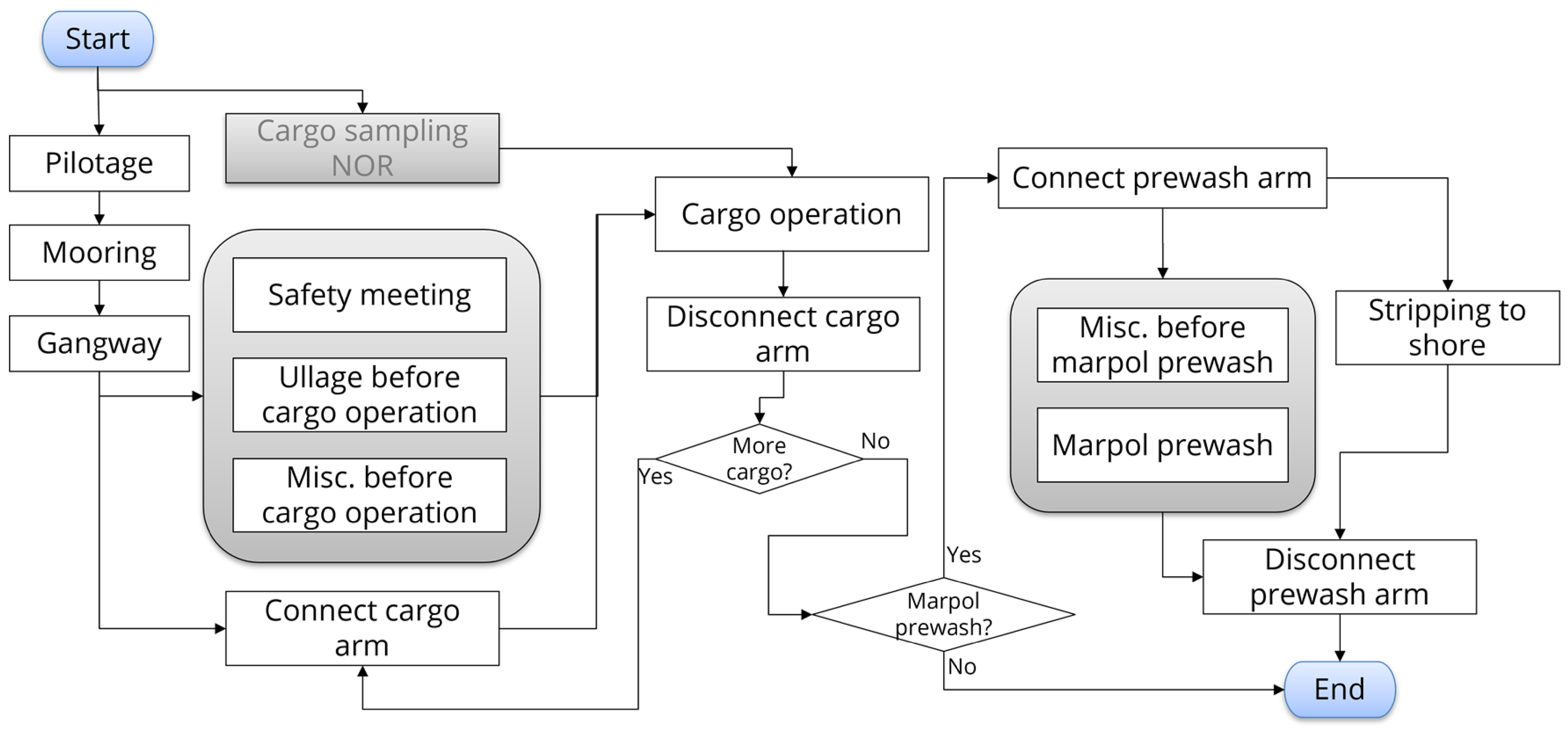

Figure 2. A generic workflow for tanker vessels' operation events (discharging)

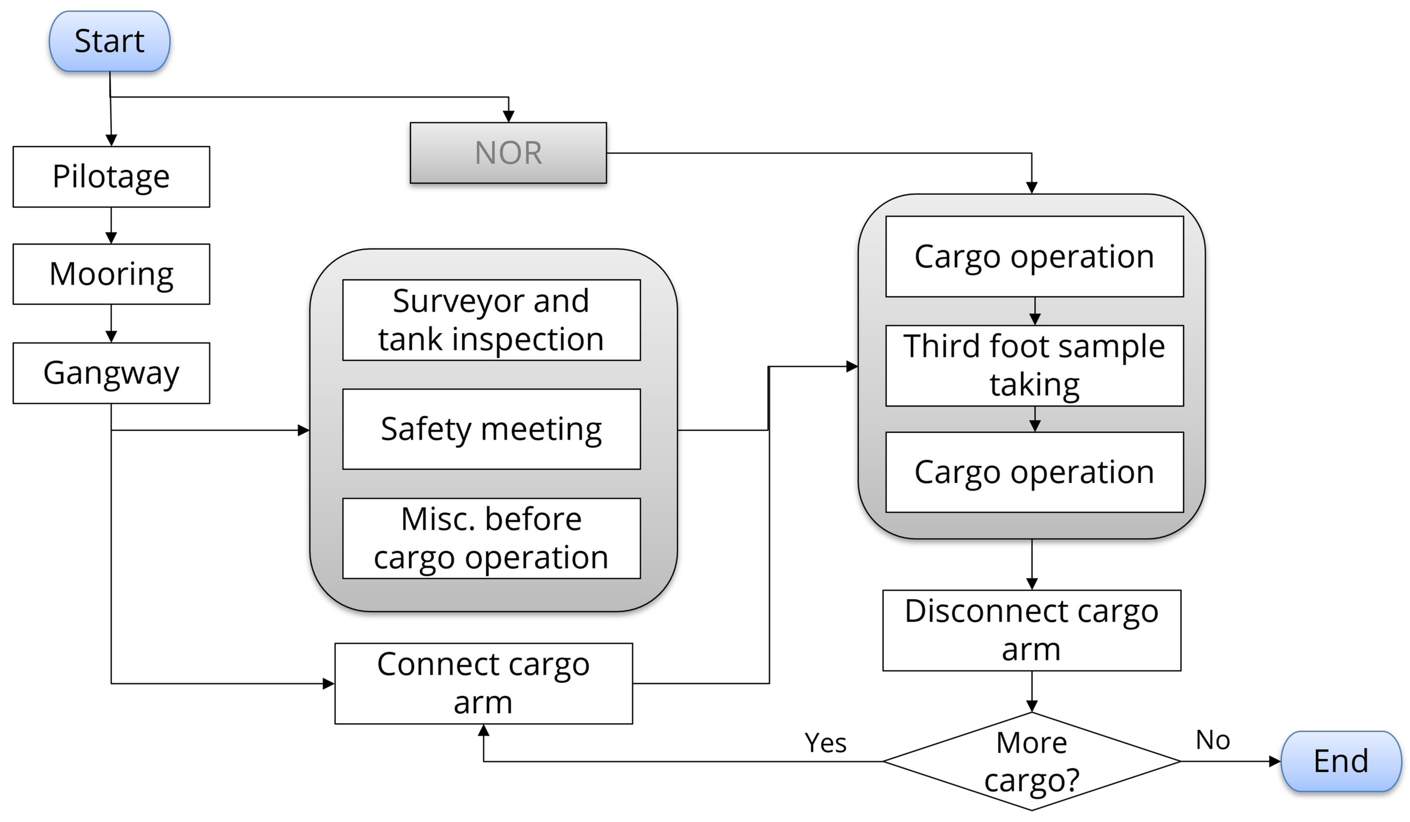

Figure 3. A generic workflow for tanker vessels' operation events (loading)

Modelling Algorithm

We have developed a model to estimate the cargo operation time for each group of cargo after conducting a thorough analysis on the cargo groups listed in Table 1. Our approach utilises Non-Linear Least Squares and takes into account a variety of factors that have been shown to significantly impact cargo operation time, such as ship length, quantity of cargo type, and cargo processing sequence. For the remaining blocks, we have formulated several statistical learning approaches to accurately estimate operation time, including Linear Regression, Multi-Decomposed Gaussian Sampling, Proportional Constant and Fixed Constant, each tailored to specific scenarios.

Evaluation and Discussion

Overall, our proposed approach is able to obtain a small Mean Absolute Error (MAE) for most cargo groups. Tables 2 and 3 present the prediction performance for the cargo operation and sampling blocks and demonstrates accurate predictions. However, the reasons for very long operations in some cases remain unclear, and due to the limited sample size, our performance for the G7 cargo type is not as favourable. More data and further research will be needed to better understand and improve the prediction accuracy for this cargo type.

Cargo Group	MAE (h)	RMSE (h)
G1	0.641	0.872
G2	1.365	1.636
G3	0.661	0.774
G4	1.891	2.144
G5	0.283	0.336
G6	1.120	1.539
G7	12.640	16.762
G8	1.549	1.837

Table 2. Cargo operation

Cargo Group	MAE (h)	RMSE (h)
G1	0.425	0.572
G2	0.861	1.032
G3	0.813	1.037
G4	1.144	0.267
G5	0.250	0.250
G6	0.667	0.729
G7	0.694	0.929
G8	0.167	0.167

Table 3. Sampling

Summary

Our proposed framework for predicting tanker berth stay involves decomposing the entire cargo process into multiple blocks, with each block modelled individually using statistical learning techniques. While our initial study shows promising results, our research is limited by the sample size of available data, and further investigation with more cargo operation data is necessary to enhance the accuracy and robustness of our predictions.

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