

Digitalisation and Predictive Modelling of Berth Stay Time Windows for Tanker Operation Enhancement (MTEC 2019)

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Motivation

- Maritime industry plays an important role in economy worldwide.
- Singapore is one of the busiest ports all over the world, where it expects more than 11,000 vessel arrivals monthly.
- Among those arrivals, over 2,000 arrivals are contributed by tanker vessels. Looking into tanker vessels is one of the focal problems in maritime study.



Images from internet







The problem statement in tanker shipping

Problem statement:

 Dis-connection and lack of intelligent coordination detrimentally impact all stakeholders (e.g. port, terminal & carrier) in operation efficiency and safety



Objective

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- To analyze patterns of tanker vessel operation, in which cargoes are transferred between terminals and vessels. Sophisticated procedures or activities have to be followed from vessel arrivals to departures.
- To predict berth stay time windows for loading and unloading operations of tanker vessels in ports.
- To provide decision support for optimizing the schedules of tanker vessels through simulation and optimization
- Provide decision supports for reducing vessels' wait time and enhancing the overall operation efficiency in ports.
- To enable potentials to improve the performance and capacity in busy ports for handling tanker vessels and enhancing service levels of terminals.





Methodology

- Firstly, the modelling framework and prototype model for the digitalization of data is proposed.
- Secondly, operation data is analyzed and data-driven predictive models are developed
 - the key factors that effectively influence the time windows of berth stays are identified and
 - predictive models are developed with key factors extracted using machine learning techniques
- Lastly, mathematical formulation of the problem and optimization for terminal operations are demonstrated.





TSO: Timing Sequential Optimizer; **MaxTFO**: Max Timing First Optimizer; **MinTFO**: Min Timing First Optimizer; **MCO**: Monte Carlo Optimizer.

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Methodology

- Digitalization model for operation data
 - According to vessel ID and their corresponding activities, the necessary data is extracted and digitalized into a standard format.
 - A prototype model with user friendly interface is developed for terminal operators to input the data via portable devices and automatically store for facilitating information retrieval and data analysis.
 - Via our developed model, the data can be digitalized in a handy manner and can nimbly be further retrieved, analyzed, calculated and updated.

YYYY - N	AIM DD	hh mm	ss	Select an activity	(Do Not Enter Value)
ihip Name:	Voyage ID:	IMO:	MMSI:	Anchorage:	100
IIL	NIL	NIL	NIL	NIL	
Operation Type Cargo Type:	Jetty (Jower Blank) Visited: NIL Cargo Volume (KL) MII	Visiting: NIL Cargo Mass (MT)	Visiti Jetty (Lower Blank) To Visiti NIL	W Operated Lanks (Upper blank) = Bu WTotal Tanks (Lower Blank): Bu NIL NIL NIL NIL	unres (WT) @Arrow (Oper Bank):
Cargo Type — Operation Break R IIL	leason: Remarks: NIL	PHL.		Record Data into Excel! Refresh to Default!	

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Mathematical Formulation

Predictive Modeling for Berth Stay:

Regression Model and machine learning model: $\hat{O}_t = a_t \cdot I_t + b_t = [\hat{o}_{t,1}, \hat{o}_{t,2}, \cdots, \hat{o}_{t,m}]^T$ Input Vector:Output Vector: I_t O_t $= [i_{t,1}, i_{t,2}, \cdots, i_{t,m}]^T$ $= [o_{t,1}, o_{t,2}, \cdots, o_{t,m}]^T$ MSE Cost Function: O_t O_t O_t O_t $I_t = \begin{bmatrix} 1 & 1 & \cdots & 1 \\ i_{t,1} & i_{t,2} & \cdots & i_{t,m} \end{bmatrix}^T$ Output Vector: $O_t = [o_{t,1}, o_{t,2}, \cdots, o_{t,m}]^T$ $= \frac{1}{m} \sum_{\substack{p=1 \ p=1}}^{m} (\hat{o}_{t,p} - o_{t,p})^2 \qquad \text{Iteratively Update:} \\ \text{Partial Derivative:} \qquad a_t^{new} = a_t^{old} - \eta \cdot \frac{\partial C}{\partial a_t} \\ \frac{\partial C}{\partial a_t} = \frac{2}{m} \sum_{\substack{p=1 \ m}}^{m} (\hat{o}_{t,p} - o_{t,p}) \cdot i_{t,p} \quad b_t^{new} = b_t^{old} - \eta \cdot \frac{\partial C}{\partial b_t} \\ \end{array}$ Model Parameters: $\begin{bmatrix} b_t \\ a_t \end{bmatrix} = (I_t^T \cdot I_t)^{-1} \cdot I_t^T \cdot O_t$ Analytic Approach Least Squares Error $\frac{\partial C}{\partial b_t} = \frac{2}{m} \sum_{j=1}^{m} (\hat{o}_{t,p} - o_{t,p})$ Iterative Approach Batch Gradient Descent Passion Agency for Made Science, Technology Possible and Research



Result

Predictive Modeling for Berth Stay:









Mathematical Formulation for Scheduling

> Objective Function Formulation: (*m* Tanker Vessels, *n* Operation-Available Terminals to minimize wait time)

Operation Duration Vector:

$$\boldsymbol{X} = [x_1, x_2, \dots, x_m]^T$$

Operation Coefficient Matrix:

$$\boldsymbol{\omega} = \begin{bmatrix} \omega_{1,1} & \omega_{1,2} & \cdots & \omega_{1,m} \\ \omega_{2,1} & \omega_{2,2} & \cdots & \omega_{2,m} \\ \vdots & \vdots & \ddots & \vdots \\ \omega_{n,1} & \omega_{n,2} & \cdots & \omega_{n,m} \end{bmatrix}$$

Buffer Time Vector:

$$\boldsymbol{T_{buffer}} = [t_1, t_2, \dots, t_n]^T$$

Total Duration for All Terminals:

$$\boldsymbol{Y} = \boldsymbol{\omega} \cdot (\boldsymbol{X} + \boldsymbol{T}_{buffer}) = [y_1, y_2, \dots, y_n]^T$$

Objective Function:

$$\boldsymbol{\omega}^* = \arg\min_{\boldsymbol{\omega}}(\max(\boldsymbol{Y}))$$

s.t. $\sum_{i=1}^n \omega_{i,j} = 1$ for $\forall j$
 $\omega_{i,j} \in \{0,1\}$ for $\forall i$ and $\forall j$

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Optimization Algorithm

Rule-Based

Rule-Based

١lg	orithm 1 Timing Sequential Optimizer (TSO)
1:	function: $TSO(X)$
2:	$X_{sorted} \leftarrow X$ (Sorted by vessels' arrival time)
3:	for $(i^{th}$ vessel in $X_{sorted})$:
4:	if $i \leq \text{TerminalNumber then}$
5:	i^{th} terminal $\leftarrow i^{th}$ vessel
6:	Update i th terminal's accumulated operation time
7:	else
8:	k th terminal has minimum accumulated operation time
9:	k^{th} terminal $\leftarrow i^{th}$ vessel
10:	Update k^{th} terminal's accumulated operation time
11:	end if
12:	end for
13:	Data visualization

Rule-Based

Algorithm 3 Min Timing First Optimizer (MinTFO)

- 1: function: MinTFO(X)
- X_{sorted} ← X (Sorted ascendingly by predicted vessels' operation time)
- 3: for $(i^{th}$ vessel in $X_{sorted})$:
- 4: if $i \leq \text{TerminalNumber then}$
- 5: i^{th} terminal $\leftarrow i^{th}$ vessel
- 6: Update *i*th terminal's accumulated operation time
- 7: else
- 8: k^{th} terminal has minimum accumulated operation time
- 9: k^{th} terminal $\leftarrow i^{th}$ vessel
- 10: Update k^{th} terminal's accumulated operation time
- 11: end if
- 12: end for
- 13: Data visualization

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Algorithm 2 Max Timing First Optimizer (MaxTFO)
1: function: MaxTFO(X)
2: $X_{sorted} \leftarrow X$ (Sorted descendingly by predicted vessels
operation time)
3: for $(i^{th}$ vessel in X_{sorted}):
4: if $i \leq \text{TerminalNumber then}$
5: i^{th} terminal $\leftarrow i^{th}$ vessel
6: Update <i>i</i> th terminal's accumulated operation time
7: else
8: k^{th} terminal has minimum accumulated operation time
9: k^{th} terminal $\leftarrow i^{th}$ vessel
10: Update k th terminal's accumulated operation time
11: end if
12: end for
13: Sort vessels by their arrival sequence in each terminal

14: Data visualization

Monte Carlo-Based

Algorithm 4 Monte Carlo Optimizer (MCO)

- 1: function: MCO(X)
- 2: for (i in iteration):
- 3: Randomly generate matrix of operation $\omega^{(i)}$
- Evaluate Y based on ω⁽ⁱ⁾

5: end for

- 6: $\omega^* \leftarrow \arg\min(\max(Y))$
- 7: Data visualization



Result (Continued)



vessel berthed to the last vessel unberthed in the port.





3200

2600

3400

3900

2000

1800

OX

SN100

ACETIC ACID

STYRENE MONOMER

D-SOL 200

PYGAS

27 28

29 30

Loading

Unloading

Unloading

Loading

Unloading

Unloading

11.545

13.7054

7.7346

14.0733

6,7379

6.5016



Conclusion

- In this study, multiple predictive models for predicting berth stay of tanker vessels are evaluated with various kinds of cargo types.
 - The results show that the volume-based least squares model outperforms others with $R^2(0.7495)$
- In this study, four optimizers for scheduling operations of tanker vessels are studied for three given simulation scenarios.
 - MaxTFO effectively outperforms the other optimizers based on the selected KPI, which indicates that the utilization efficiency of terminals.
 - MCO is more applicable for narrow window cases (i.e. when the information of future vessel and cargo is relatively limited).
- A number of assumptions have to be highlighted in this study
 - Assumptions made for research simplicity purpose, some aspects in practical maritime operations are not taken into considerations, such as multiple-cargo, multiple-terminal visit, etc.
 - These are the tasks of our near future research in the field of maritime.







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Thanks! Q&A





