Artificial Intelligence for Port State Control and Case Study for Hong Kong

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Acknowledgments

- This research is sponsored by Hong Kong Policy Innovation and Co-ordination Office and Hong Kong Research Grants Council.
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- Comments from the following practitioners are highly appreciated: Captain Z. Ni, Mr. Chiu-sum Mok, Senior Surveyor Mr Z.H. Huang, Senior Surveyor Mr Meng Gong, Dr. Stephen Li, Captain Jian Feng Zhou, Captain Chang Zheng Chen, Captain Hongpeng Liu, Captain Zhang, and Mr Tim T.Y. Wang

1. Introduction

maritime transportation

Objectives

- Reduce maritime risks
- Protect marine environment
- Guarantee good working and living conditions for the crew.

International rules and recommendations

❑ **SOLAS**:
Sets minimal safety standards in the construction, equipment and operation of merchant ships.

❑ **MARPOL**:
Aims to minimize pollution of the oceans and seas, including dumping, oil and air pollution.

❑ **STCW**:
Sets minimum qualification standards for masters, officers and watch personnel on seagoing merchant ships and large yachts.

Substandard ships

Ships cannot comply with the conventions.

Flag state

"first line of defense",

unable to perform well

Port state Control

"second line of defense"

"last safety net"

maritime safety

Example of inspection records of the Port of HK in the database

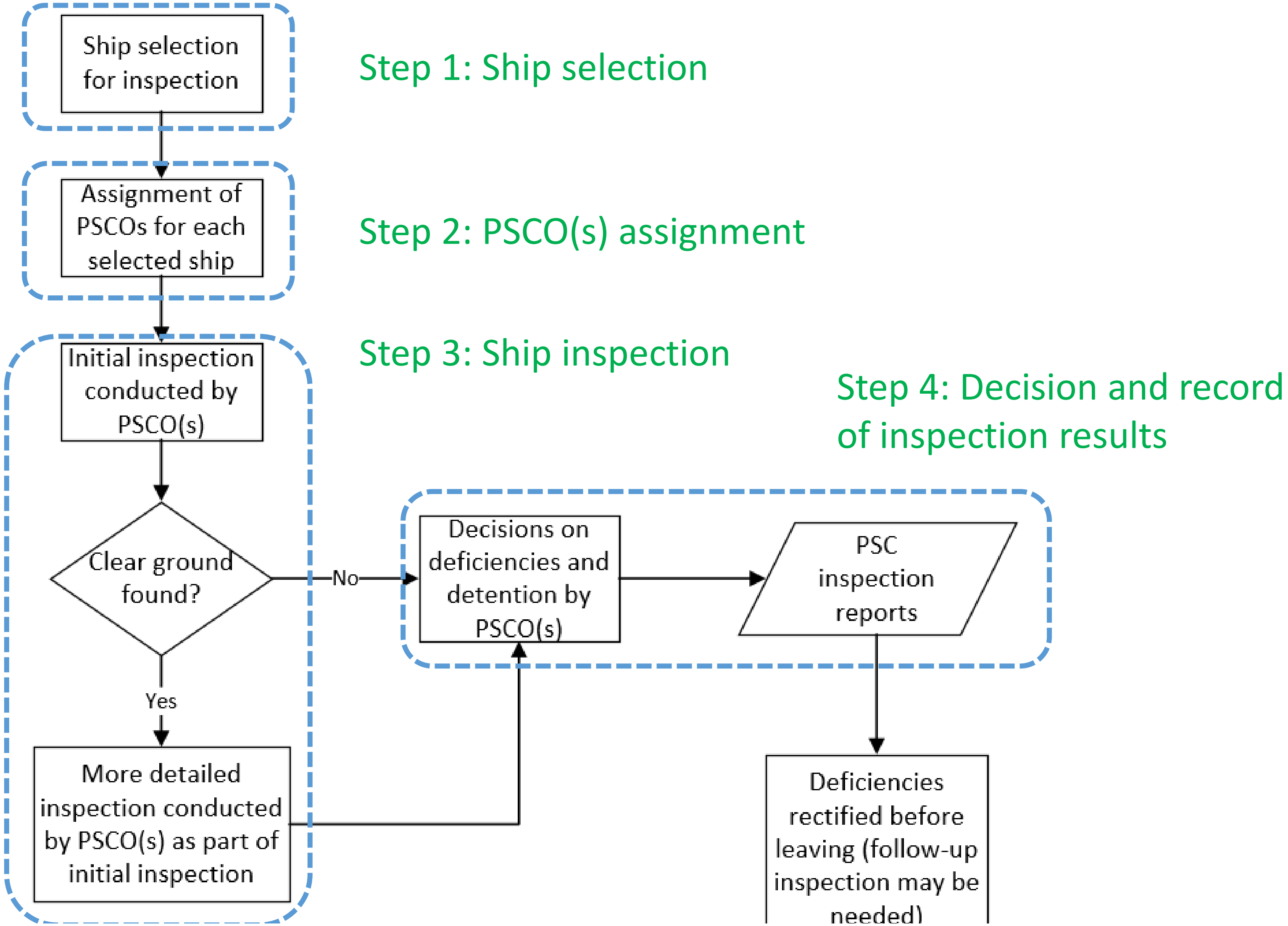


Figure 2. Example of inspection records of the Port of HK in the database

Source: http://www.tokyo-mou.org/inspections_detentions/psc_database.php

Code	Deficiency item	Code	Deficiency item	Code	Deficiency item
D1	Certificates and documentation	D7	Fire safety	D13	Propulsion and auxiliary machinery
D2	Structural condition	D8	Alarms	D14	Pollution prevention
D3	Water/Weathertight condition	D9	Working and living conditions	D15	ISM
D4	Emergency system	D10	Safety of navigation	D18	Labour conditions
D5	Radio communication	D11	Life saving appliances	D99	Other
D6	Cargo operations including equipment	D12	Dangerous goods		

MEMORANDUM OF UNDERSTANDING ON PORT STATE CONTROL IN THE ASIA-PACIFIC REGION

INSPECTIONS SEARCH RESULTS

Found 2133 elements in 85 page(s). Pages from 2126 to 2133

Legend: □ - initial inspection ■ - follow-up inspection

Type	Date	Place	IMO number	Ship Name	Callsign	MMSI	Flag	Deficiencies (□: recorded/ ■: for checking)	Detention	Ship Risk Profile at the time of inspection
□	04.01.2017	Hong Kong (Hong Kong, China)	9279214	BIENDONG MARINER	3WKL	574260000	Vietnam	8	no	High Risk Ship
■	04.01.2017	Hong Kong (Hong Kong, China)	9279214	BIENDONG MARINER	3WKL	574260000	Vietnam	12	no	
□	03.01.2017	Hong Kong (Hong Kong, China)	8415873	XIANG SHENG	9LU2451	667001648	Sierra Leone	41	yes	High Risk Ship
□	03.01.2017	Hong Kong (Hong Kong, China)	8611752	SHENG HO	BNJG	416357000	Taiwan, Province of China	11	no	High Risk Ship
□	03.01.2017	Hong Kong (Hong Kong, China)	9316373	STAR RIVER	3FTA3	372701000	Panama	3	no	Standard Risk Ship
□	03.01.2017	Hong Kong (Hong Kong, China)	9159842	PRINCESS OF LUCK	5BGF3	209735000	Cyprus	2	no	High Risk Ship
■	03.01.2017	Hong Kong (Hong Kong, China)	7215161	METROPOLIS	6YRN7	339300690	Jamaica	11	no	
■	03.01.2017	Hong Kong (Hong Kong, China)	9159842	PRINCESS OF LUCK	5BGF3	209735000	Cyprus	1	no	

Start new search

MEMORANDUM OF UNDERSTANDING ON PORT STATE CONTROL IN THE ASIA-PACIFIC REGION

Inspection data

Date	Authority	Port	Type	Detention
31.12.2019	Hong Kong, China	Hong Kong	initial	no

Ship data

Ship Name	IMO number	MMSI	Callsign	Classification Society	Flag	Type	Date keel laid	Deadweight	Tonnage
GRAND MIDAS	9044138	667001506	9LU2309	Overseas Marine Certification Services	Sierra Leone	Container ship	1992-04-23		3986

Company details

Name	IMO number	Residence	Registered	Phone	Fax	Email
VAST OCEAN GLOBAL LTD	6033544	Seychelles	Seychelles			

Ship deficiencies

#	Code	Nature	Ground for detention
1	10109	SAFETY OF NAVIGATION (Lights, shapes, sound-signals)	No
2	07110	FIRE SAFETY (Fire fighting equipment and appliances)	No
3	03105	WATER/WEATHERTIGHT CONDITIONS (Covers (hatchway-, portable-, tarpaulins, etc.))	No
4	10136	SAFETY OF NAVIGATION (Estabilishment of working language onboard)	No
5	10127	SAFETY OF NAVIGATION (Voyage or passage plan)	No
6	05118	RADIO COMMUNICATIONS (Operation of GMDSS equipment)	No
7	09204	LIVING AND WORKING CONDITIONS - WORKING CONDITIONS (Safe means of access)	No
8	01315	CERTIFICATE AND DOCUMENTATION - DOCUMENTS (Oil record book)	No

Certificates

Code	Nature	Issuing Authority/RO	Date of issue	Date of expire	Surveying Authority/RO	Date of survey	Surveyed Port
501	Cargo Ship Safety Construction	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
502	Cargo Ship Safety Equipment	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
503	Cargo Ship Safety Radio	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
505	International Oil Pollution Prevention (IOPP)	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
506	International Air Pollution Prevention	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
507	International Sewage Pollution Prevention	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
508	Load Line	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
509	Document of Compliance	New United International Marine Services Ltd. (250)	20.05.2019	19.05.2020			
510	Safety Management Certificate	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
512	Minimum Safe Manning Document	Sierra Leone (SL)	18.10.2019				
528	International Ballast Water Management	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			
529	International Anti-Fouling System	Overseas Marine Certification Services (216)	27.10.2019				
532	International Energy Efficiency (IEE)	Overseas Marine Certification Services (216)	27.10.2019				
533	Maritime Labour Certificate	Overseas Marine Certification Services (216)	27.10.2019	26.03.2020			

Example of deficiencies detected by the PSC authority

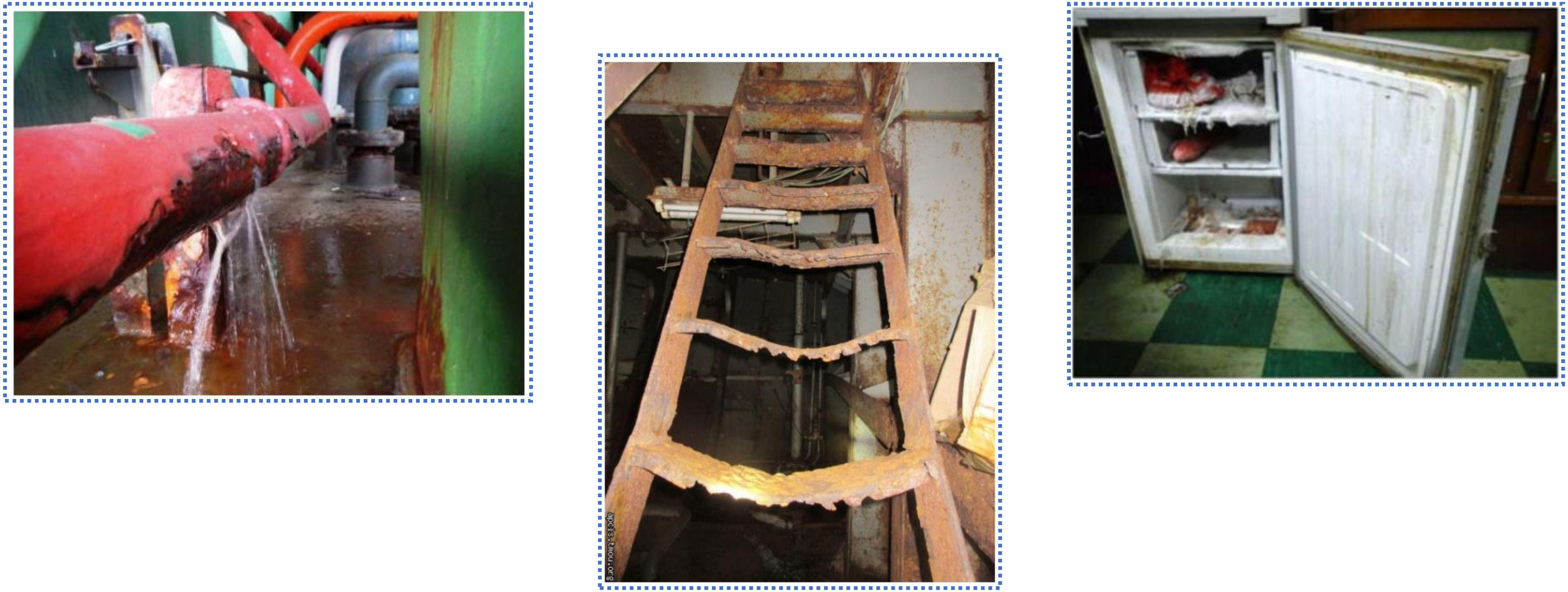


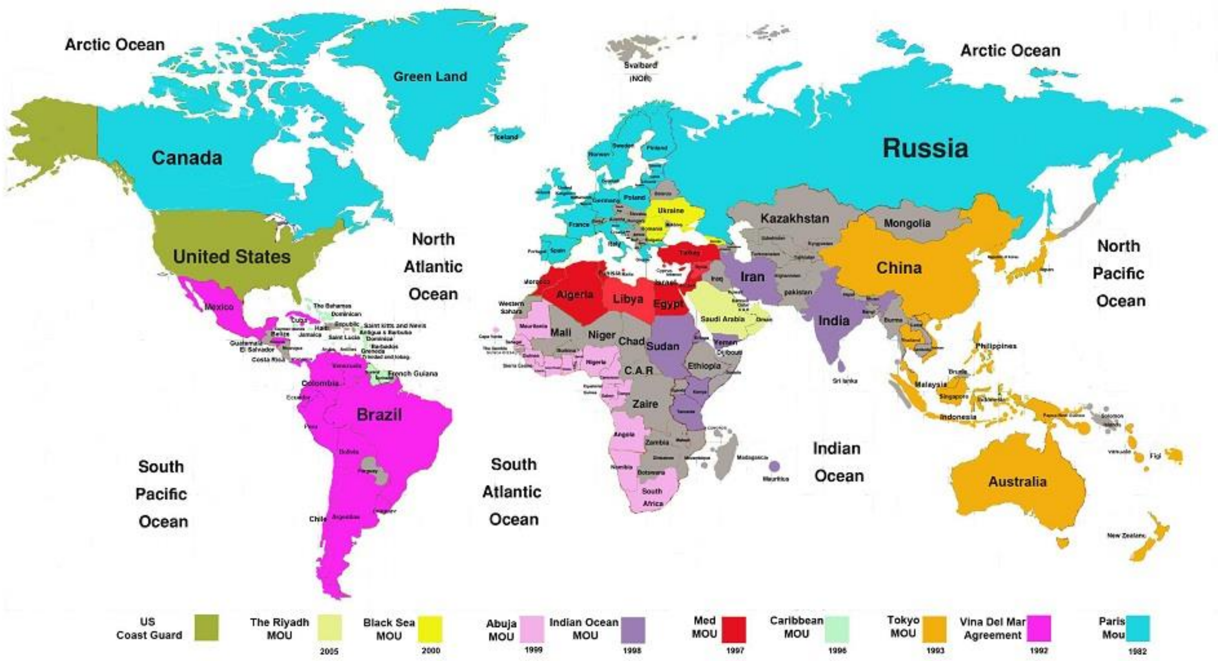
Figure 3. Example of deficiencies detected by the PSC authority

Source: Tokyo MoU, 2017; Tokyo MoU, 2018ba

2. Current Ship Selection Scheme in PSC Inspection

Regional Memorandum of Understanding (MoU)

- Nine current regional MoUs: Abuja MoU, Vina del Mar MoU, Black Sea MoU, Caribbean MoU, Indian Ocean MoU, Mediterranean MoU, Paris MoU (established in 1982), Tokyo MoU, and Riyadh MoU
- The United States Coast Guard (USCG) maintains the tenth inspection regime.



https://cleanship.se/psc/index

Tokyo MOU

- Tokyo MOU: a New Inspection Regime (NIR) for selection of ships has been introduced from 1 January 2014.
- The concept of the NIR of the Tokyo MOU is similar to that of the Paris MOU introduced since 2011.

NIR

Ship risk profile	Time window (months)
LRS	9 to 18
SRS	5 to 8
HRS	2 to 4

Ship Risk Profile (SRP) ship selection scheme

Ship Risk Profile sheet

Ship Risk Profile

Parameters		High Risk Ship (HRS) (When sum of weighting points >=4)		Standard Risk Ship (SRS)	Low Risk Ship (LRS)
		Criteria	Weighting points	Criteria	Criteria
Type of Ship		Chemical tanker, Gas Carrier, Oil tanker, Bulk carrier, Passenger ship	2	Neither LRS nor HRS	-
Age of Ship		All types > 12y	1		-
Flag	BGW-list[1]	Black	1		White
	VIMSAS[2]	-	-		Yes
Recognized Organization	RO of Tokyo MOU[3]	-	-		Yes
	Performance[4]	Low Very Low	1		High
Company performance[5]		Low Very Low	2		High
Deficiencies	Number of deficiencies recorded in each inspection within previous 36 months	How many inspections were there which recorded over 5 deficiencies?	No. of inspections which recorded over 5 deficiencies		All inspections have 5 or less deficiencies (at least one inspection within previous 36 months)
Detentions	Number of Detention within previous 36 months	3 or more detentions	1		No detention

Ship generic factors

Ship inspection historical factors

(Tokyo MoU, 2014)

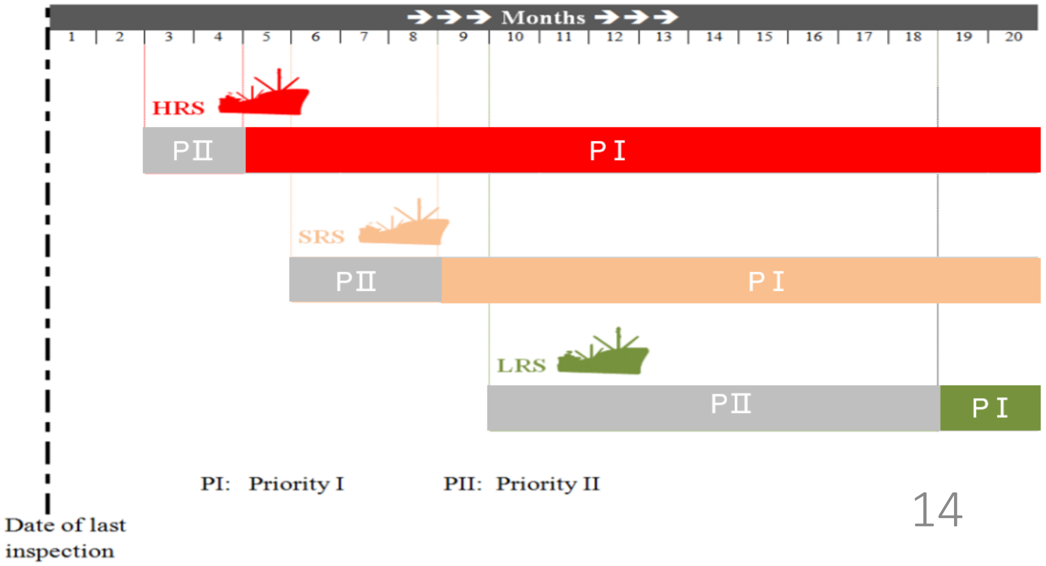
Three risk types of ships

High risk ship (**HRS**): Ships with the sum of the weighting points >=4.

Low risk ship (**LRS**): Ships meet all the criteria.

Standard risk ship (**SRS**): Ships that are neither HRS nor LRS.

Inspection time window



Parameter	Calculation method	States from best to worst
Ship flag performance	Established annually by taking its ships' inspection and detention conditions over the preceding three calendar years into account. Black-grey-white ship flag lists are published in an MoU's annual report.	White Grey Black
Ship recognized organization (RO) performance	Established annually considering their ships' inspection and detention history over the preceding three calendar years. The RO performance list is published in an MoU's annual report.	High Medium Low Very low
Ship company performance	Established based on the ships detention and deficiency history calculated daily on the basis of a running 36-month period	High Medium Low Very low

NIR

- ***Priority I++*** (ships with overriding factors)
  - Have the highest priority to be inspected
- ***Priority I+*** (ships with no inspection record in Tokyo MoU)
  - Should be inspected
- ***Priority I*** (ships out of the time windows)
  - Should be inspected
- ***Priority II*** (ships within the time windows)
  - Can be inspected
- ***Priority None*** (ships not entering the time windows)
  - Should not be inspected unless with overriding factors

Tokyo MoU Annual Report 2019

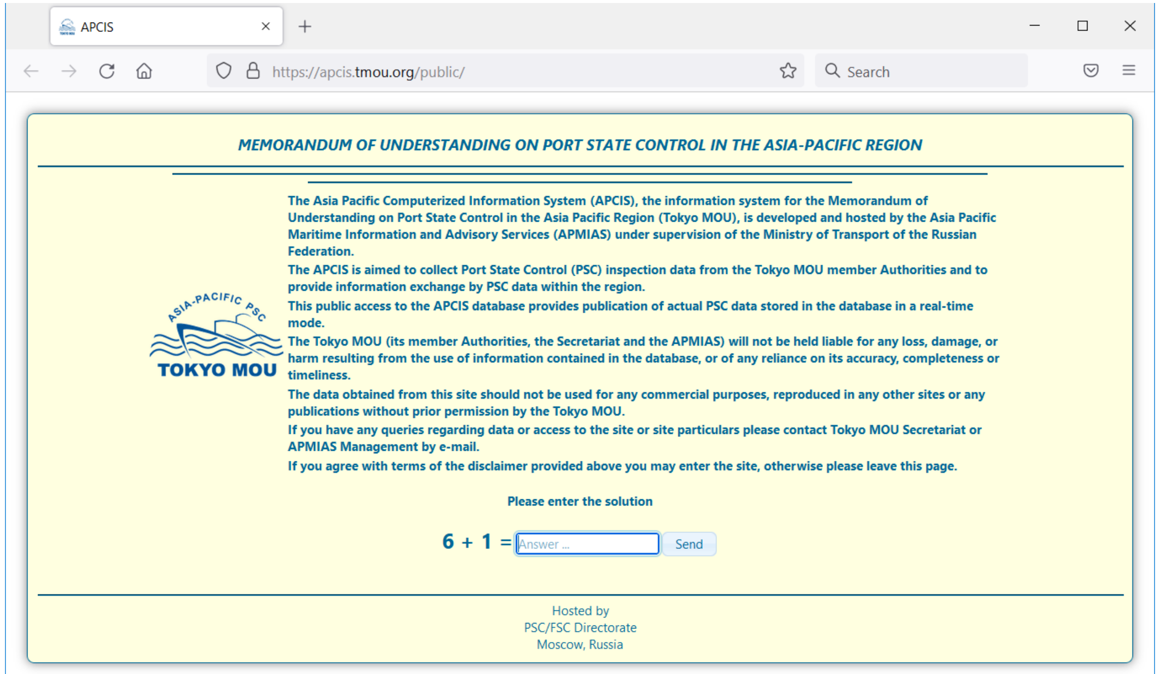
- In 2019, 31,372 inspections, involving 17,647 individual ships, were carried out on ships registered under 97 flags
- Out of 31,372 inspections, there were 18,461 inspections where ships were found with deficiencies.
- Since the total number of individual ships operating in the region was estimated at 25,741, the inspection rate in the region was approximately 69% in 2019
- In 2019, 983 ships were detained due to serious deficiencies having been found onboard. The detention rate of ships inspected was 3.13%.

Hong Kong PSC

- From 2015 to 2017, there were a total of 10,239 individual ships visiting the port of Hong Kong and 1,324 of them were actually inspected
- The inspection rate of individual ships at Hong Kong over 2017–2019 was 13%, which is slightly less than the target rate of 15% by Tokyo MoU.
- The detention rate at Hong Kong is higher than the average of Tokyo MoU.

Motivation

- The current NIR ship selection rule is elementary. State-of-the-art development in AI should be taken advantage of.
- The PSC records are publicly available
  - https://apcis.tmou.org/public/



3. Artificial Intelligence (AI) for Predicting Overall Ship Conditions

Motivation

- ***Priority I++*** (ships with overriding factors)
  - Have the highest priority to be inspected
- ***Priority I+*** (ships with no inspection record in Tokyo MoU)
  - Should be inspected
- ***Priority I*** (ships out of the time windows)
  - Should be inspected
- ***Priority II*** (ships within the time windows)
  - Can be inspected
- ***Priority None*** (ships not entering the time windows)
  - Should not be inspected unless with overriding factors

- With limited PSC manpower, limited time spent at port by ship, and possibility of a sudden arrival of a huge number of foreign-flagged ships, not all ships in Priorities I++, I+, and I will be inspected.
- In short term, AI can provide decision support for PSC authority regarding i) among ships of Priority I, which one has the worst condition? ii) among ships of Priority II, which one has the worst condition?
- In long term, AI-based inspection regimes can be adopted at an MoU

3.1 Predict number of deficiencies

3.1.1 Predict number of deficiencies without considering domain knowledge

Tree Augmented Naive Bayes (TAN) Classifier Model

Input data

Case data set

250 PSC inspection records ranging from January 2017 to July 2017 at the Port of Hong Kong to train the model

Another 50 records are used for testing

10 variables

Ship generic factors

- ship age
- ship gross tonnage
- ship type
- ship flag
- ship company
- ship recognized organization

Ship dynamic factors

- number of changing flag times

Ship inspection historical factors

- number of previous detention times
- last inspection time,
- number of deficiencies in last inspection

Class variable

number of deficiencies

Variable	Unit	Type	Node name	States
Number of deficiencies		discrete	deficiency_no	S1:0to2, S2:3to6, S3:7+
Ship age	year	discrete	age	S1:0to7, S2:8to12, S3:13+
Ship gross tonnage	100 cubic feet	continuous	GT	S1:0to11228, S2:11229to40053, S3:40054+
Number of previous detention times		discrete	pre_detention	S1:zero, S2:one, S3:2+, S4:none
Last inspection time	month	continuous	last_inspection	S1:0to5.5, S2:5.6to9.6, S3:9.7+, S4:none
Number of deficiencies in last inspection		discrete	last_deficiency_no	S1:zero, S2:1to3, S3:4+, S4:none
Number of changing flag times		discrete	change_flag	S1:zero, S2:one, S3:2+, S4:none
Ship type		nominal data	type	S1:bulk_carrier, S2: container_ship, S3:general_cargo/multipurpose, S4:passenger_ship, S5:tanker, S6:other
Ship flag		ordinal data	flag	S1:white, S2:grey, S3:black, S4:not_listed
Ship company		ordinal data	company	S1:high, S2:medium, S3:low, S4:very_low
Ship recognized organization		ordinal data	RO	S1:high, S2:medium, S3:low, S4:not_listed

TAN classifier (new parameters)

Ship generic factors

- ship age
- ~~ship gross tonnage~~
- ship type
- ship flag
- ship company
- ship recognized organization

Ship dynamic factors

- ~~number of changing flag times~~

Ship inspection historical factors

- number of previous detention times
- ~~last inspection time,~~
- number of deficiencies in last inspection

TAN classifier (old parameters in SRP)

Ship generic factors

- ship age
- ship type
- ship flag
- ship company
- ship recognized organization

Ship inspection historical factors

- number of previous detention times
- number of deficiencies in last inspection

How to validate the effectiveness of the AI model?

- Impractical Validation 0:
  - On a past day, ships ABC are actually inspected, but the AI model recommends ships ABD. Then, compare the number of deficiencies of ship C with the number of deficiencies of D.
  - Challenge: we never know the number of deficiencies of the ships that are not inspected.

How to validate the effectiveness of the AI model?

- Validation 1: A PSC authority implements the AI model for one year
  - Compare the average number of deficiencies per inspection before and after implementing the AI model
    - However, things may change with time (ships are more compliant)
    - A DiD approach can address it
- Validation 2: Each day, a PSC authority selects e.g., 3 ships (e.g., ABC), the AI model recommends 3 ships (e.g., ABD), all the four ships are inspected and the number of deficiencies of ship C is compared with the number of deficiencies of D.

How to validate the effectiveness of the AI model?

- Practical Validation 3:
  - We collected 300 historical inspection records
  - We used 250 records to train the AI model and the remaining 50 to validate
    - Suppose these 50 ships arrive at Hong Kong on the same day
    - For each i=1,2,3,…,50
      - Suppose the Marine Department can only inspect i ships
      - We use the Tokyo MoU rule to select i ships, and calculate their total number of deficiencies
      - The AI model recommends i ships, and we calculate their total number of deficiencies
      - Compare the above two numbers

SRP Inspection List

Priority I+ (ships with no inspection before)

a. High risk ship
b. Standard risk ship
c. Low risk ship

*Ships in the same SRP are randomly selected

Priority I (ships out of the time window)

Descending order in ship risk index

*Ships in the same risk index are randomly selected

Priority II (ships within the time window)

Descending order in ship risk index

*Ships in the same risk index are randomly selected

Priority None (ships do not enter the time window)

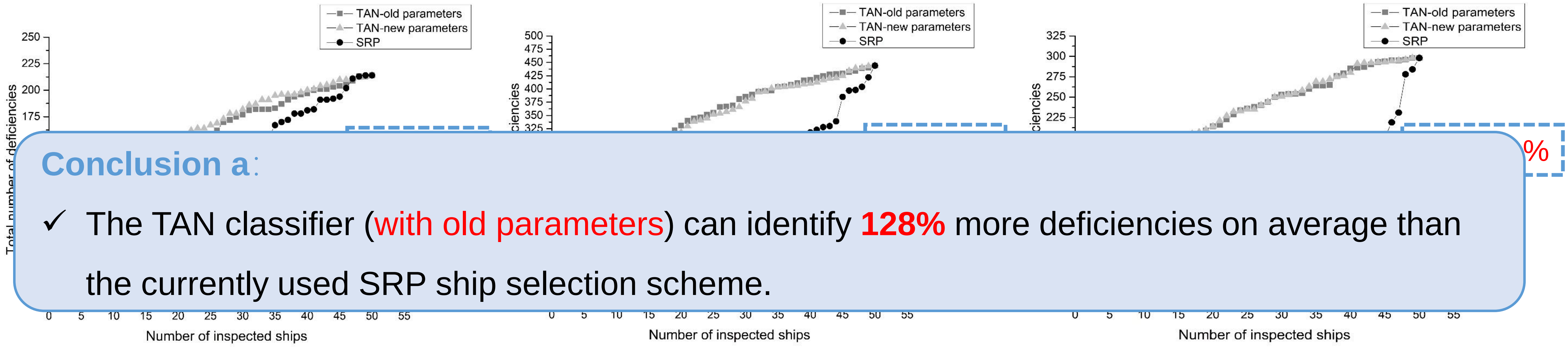
Descending order in ship risk index

*Ships in the same risk index are randomly selected

Table 1: Calculation of ship risk index

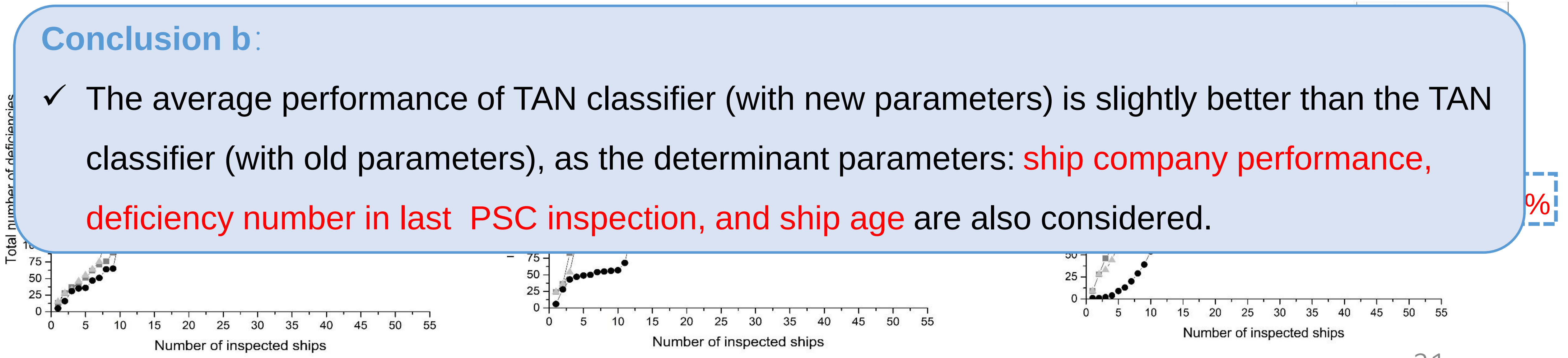
Ship risk profile	Time window (months)	State of time window		
		out of time window	within time window	time window closed
LRS	9 to 18	$RI = \frac{L_i}{9}$	$RI = \frac{L_i - 9}{18 - 9}$	$RI = \frac{L_i}{18}$
SRS	5 to 8	$RI = \frac{L_i}{5}$	$RI = \frac{L_i - 5}{8 - 5}$	$RI = \frac{L_i}{8}$
HRS	2 to 4	$RI = \frac{L_i}{2}$	$RI = \frac{L_i - 2}{4 - 2}$	$RI = \frac{L_i}{4}$

Numerical experiments



Conclusion a:

✓ The TAN classifier (with old parameters) can identify **128%** more deficiencies on average than the currently used SRP ship selection scheme.



Conclusion b:

✓ The average performance of TAN classifier (with new parameters) is slightly better than the TAN classifier (with old parameters), as the determinant parameters: ship company performance, deficiency number in last PSC inspection, and ship age are also considered.

3.1.2 Predict number of deficiencies considering domain knowledge

Basic idea: Given all other conditions equal, a ship with worse flag/company/RO performance should be predicted to have a larger number of deficiencies.

- Extreme Gradient Boosting (XGBoost) Model

Input: Ship static properties, ship dynamic properties, and historical inspection condition in TMoU
Output: The total number of deficiencies of a ship

Increase in predicted deficiency number of consecutive states

State change	Flag performance	State change	RO performance	Company performance
White->Grey	0.8030	High->Medium	0.2530	0.5312
Grey->Black	0.2236	Medium->Low	0 (no such data)	0.7787
		Low->Very low	\	1.4919

Model Performance: Mean absolute error (MAE) is 2.372, mean squared error (MSE) is 12.470.

Yan R., Wang S., Cao J., Sun D., 2021. Shipping domain knowledge informed prediction and optimization in port state control. Transportation Research Part B: Methodological 149, 52-78.

3.1.3 Explainable AI model for predicting number of deficiencies

Explainable Gradient Boosting Regression Tree (GBRT) model

- The same seven features as the NIR are used

Feature importance on the predicted deficiency number

Binary feature
1_ship_type_concerned (x_1^T)
2_ship_age_12+ (x_2^T)
3_flag_black (x_3^T)
4_RO_low (x_4^T)
5_company_low (x_5^T)
7_detention_last_36 (x_7^T)

The while-box surrogate model for explanation

$$\hat{y}_i^T = 4.112735 + \left\{ \begin{array}{l} x_1^{T,i} \times (-0.4454) + (1 - x_1^{T,i}) \times 2.3722 + x_2^{T,i} \times 0.8501 + (1 - x_2^{T,i}) \times (-0.4540) + \\ x_3^{T,i} \times 3.1336 + (1 - x_3^{T,i}) \times (-0.1342) + x_5^{T,i} \times 1.7802 + (1 - x_5^{T,i}) \times (-0.4434) + \\ x_7^{T,i} \times 2.1108 + (1 - x_7^{T,i}) \times (-0.0307) + \left[-0.8871 + 1.6953 \times \sqrt{x_6^T} \right] \end{array} \right\}$$

Model Performance: Mean absolute error (MAE) is 2.791, mean squared error (MSE) is 18.483.

Yan R., Wu S., Jin Y., Cao J., Wang S., 2021. Efficient and explainable ship selection planning in port state control. Submitted to Transportation Research Part B: Methodological, under review.

3.2 Predict probability of detention

Balanced Random Forest (BRF) model considering data imbalance

Input: Ship static properties, ship dynamic properties, and historical inspection condition in TMoU

Output: The detention risk (expressed by a probability) of a ship

Model Performance: 85% of the detained ships can be accurately identified;
61% of the ships predicted to be detained are actually detained

Yan R., Wang S., Peng C., 2021. An articial intelligence model considering data imbalance for ship selection in port state control based on detention probabilities. Journal of Computational Science 48, 10125

3.3. AI for Predicting Ship Conditions

Models: Ship deficiency number predicted by BN model; ship detention predicted by BRF model

Input: Ship static properties, ship dynamic properties, and historical inspection condition in TMoU
Output: Ship overall risk considering ship deficiency number (60% weight) and detention probability (40% weight)
https://sites.google.com/site/wangshuaian/research-interest/ai-for-psc-at-hong-kong

AI for PSC at Hong Kong

Return

This system downloads the information of ships at the Port of Hong Kong and applies an artificial intelligence (AI) model developed by The Hong Kong Polytechnic to predict the conditions (number of deficiencies and probability of detention) of foreign-flagged ships, so that the Marine Department of Hong Kong can select th worst conditions for Port State Control (PSC) inspection.

Info about the project

The table below is updated at around 8:55am (Hong Kong time) every day. For more frequent updates every 15 min, download the up-to-date prediction results (x

Candidate ships for PSC inspection at Hong Kong : Sheet1

2021-09-25 08:55:00 ships at port for inspection

Note: Column O is a weighted sum of Column M and Column N
Data source: MD (Marine Department)
TMoU (Tokyo MoU website)
AI (Artificial Intelligence model developed by the PolyU team)

MD Call Sign	TMoU IMO number	MD Vessel Name	MD Ship Type	MD Flag	MD Last port of call	MD Name of agent	MD Current location	TMoU Ship risk profile	TMoU Inspection Priority	TMoU Date of last inspection	TMoU Date of inspection time window	AI Predicted deficiency number	AI Predicted detention probability	AI Predicted risk factor	AI Recommended inspection rank by AI
9M2385	9872236	MTT SAPA	CONTAINE	Malaysia	NANSHA,	CMA CGM	KWAICHUN	SRS	No inspection record						0
3FYH5	9140592	RUN FAR	LIQUIFIE	Panama	SHENZHEN	S5 ASIA	SOUTH LA	HRS	Out of t	2020/01/	2020/03/	1.31	2.44	1.76	1
3WVF7	9352688	HAIAN GA	CONTAINE	Vietnam	KEELUNG	HYALINE SHIPPING		HRS	Out of t	2019/12/	2020/02/	1.3	0.6	1.02	2
9V2196	9385025	WAN HAI	CONTAINE	Singapor	SHEKOU,	HYALINE	KWAICHUN	SRS	Out of t	2019/12/	2020/05/	0.6	0.58	0.59	3
9HA5044	9450612	CMA CGM	CONTAINE	Malta	SHEKOU,	CMA CGM	KWAICHUN	SRS	Out of t	2019/09/	2020/02/	0.54	0.51	0.53	4
D5WR2	9864540	YM CAPAC	CONTAINE	Liberia	OPEN SEA	YANG MIN	KWAICHUN	SRS	Out of t	2020/11/	2021/04/	0.52	0.16	0.38	5
9V2196	9385025	HYUNDAI	CONTAINE	Singapor	SHEKOU,	HMM (HONG KONG) I		SRS	Out of t	2019/12/	2020/05/	0.54	0.11	0.37	6

Yan R., Wang S., Peng C., 2021. Ship selection in port state control: Status and perspectives. Maritime Policy & Management, DOI: 10.1080/03088839.2021.1889067.

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3FYH5	9140592	RUN FAR	LIQUIFIE	Panama	SHENZHEN	S5 ASIA	SOUTH LA	HRS	Out of t	2020/01/	2020/03/	1.31	2.44	1.76	1
3WVF7	9352688	HAIAN GA	CONTAINE	Vietnam	KEELUNG	HYALINE SHIPPING		HRS	Out of t	2019/12/	2020/02/	1.3	0.6	1.02	2
9V2196	9385025	WAN HAI	CONTAINE	Singapor	SHEKOU,	HYALINE	KWAICHUN	SRS	Out of t	2019/12/	2020/05/	0.6	0.58	0.59	3
9HA5044	9450612	CMA CGM	CONTAINE	Malta	SHEKOU,	CMA CGM	KWAICHUN	SRS	Out of t	2019/09/	2020/02/	0.54	0.51	0.53	4
D5WR2	9864540	YM CAPAC	CONTAINE	Liberia	OPEN SEA	YANG MIN	KWAICHUN	SRS	Out of t	2020/11/	2021/04/	0.52	0.16	0.38	5
9V2196	9385025	HYUNDAI	CONTAINE	Singapor	SHEKOU,	HMM (HONG KONG) I		SRS	Out of t	2019/12/	2020/05/	0.54	0.11	0.37	6

4. AI for Predicting Ship Detailed Conditions

Motivation

- Predicting the detailed conditions (e.g., chance of deficiencies of each code) can help
  - PSC officer to conduct more efficient inspection
  - Ship management companies to carry out effective maintenance plans, reducing costs and avoiding deficiencies and detention

4.1. Predicting Each Deficiency Code

Ship specific risk prediction

Basic idea: Prediction of the number of deficiencies under each deficiency code in PSC.

Code	Deficiency item	Code	Deficiency item	Code	Deficiency item
D1	Certificates and documentation	D7	Fire safety	D13	Propulsion and auxiliary machinery
D2	Structural condition	D8	Alarms	D14	Pollution prevention
D3	Water/Weathertight condition	D9	Working and living conditions	D15	ISM
D4	Emergency system	D10	Safety of navigation	D18	Labour conditions
D5	Radio communication	D11	Life saving appliances	D99	Other
D6	Cargo operations including equipment	D12	Dangerous goods		

Yan R., Wang S., Fagerholt K., 2020. A semi-\smart predict then optimize" (semi-SPO) method for efficient ship inspection. Transportation Research Part B: Methodological 142, 100{125.

4.2. Association between Different Deficiencies

Association rule mining in ship deficiency items

Basic idea: a) identify the deficiency items that are frequently detected together in one inspection; b) mine association rules from the inspection records

Model: association rule mining based on a-priori algorithm

Input: deficiency items identified in PSC inspection records at the HK port from January 1 2018 to June 2018

Output: frequent item sets and association rules of deficiency items

Frequent item sets: sets of deficiency items that are often detected in on inspection

Large 1-intemset	Support
{D7 - Fire safety}	0.55
{D10 - Safety of navigation}	0.45
{D11 - Life saving appliances}	0.40
{D9 - Working and living conditions}	0.39
{D3 - Water/Weathertight condition}	0.33
{D14 - Pollution prevention}	0.30
{D1 - Certificates and documentation}	0.29
{D5 - Radio communication}	0.15
{D4 - Emergency system}	0.14
{D8 – Alarms}	0.11
{D13 - Propulsion and auxiliary machinery}	0.10

Large 2-intemset	Support	Large 2-intemset	Support	Large 2-intemset	Support
{D7, D10}	0.28	{D1, D7}	0.17	{D3, D9}	0.15
{D7, D11}	0.24	{D3, D10}	0.17	{D3, D14}	0.13
{D7, D9}	0.23	{D9, D11}	0.17	{D1, D14}	0.11
{D10, D11}	0.21	{D1, D10}	0.17	{D4, D11}	0.10
{D7, D14}	0.19	{D1, D11}	0.17	{D9, D14}	0.10
{D9, D10}	0.19	{D3, D11}	0.16	{D1, D9}	0.10
{D3, D7}	0.18	{D11, D14}	0.16	{D1, D3}	0.10
{D10, D14}	0.18				

Large 3-intemset	Support	Large 3-intemset	Support	Large 3-intemset	Support
{D7, D10, D11}	0.14	{D10, D11, D14}	0.12	{D1, D7, D11}	0.10
{D7, D9, D10}	0.13	{D3, D10, D11}	0.11	{D1, D10, D14}	0.10
{D7, D10, D14}	0.13	{D7, D9, D11}	0.11	{D3, D7, D11}	0.10
{D1, D7, D10}	0.12	{D1, D10, D11}	0.11	{D3, D7, D10}	0.10
{D7, D11, D14}	0.12				

Yan R., Zhuge D., Wang S., 2021. Development of two highly-ecient and innovative inspection schemes for PSC inspection. Asia-Pacic Journal of Operational Research 38(3), 2040022.

Association rules derived from frequent item sets

Rule NO.	Left-hand side	Right-hand side	Confidence	Lift	Rule NO.	Left-hand side	Right-hand side	Confidence	Lift
1	D1, D14	D10	0.91	2.03	12	D7, D14	D10	0.66	1.49
2	D11, D14	D10	0.77	1.72	13	D7, D14	D11	0.65	1.61
3	D11, D14	D7	0.77	1.40	14	D1, D10	D11	0.64	1.58
4	D4	D11	0.74	1.83	15	D1, D11	D10	0.64	1.43
5	D1, D10	D7	0.74	1.34	16	D3, D10	D11	0.63	1.55
6	D1, D7	D10	0.73	1.62	17	D10, D11	D14	0.61	2.02
7	D10, D11	D7	0.72	1.30	18	D1, D7	D11	0.61	1.50
8	D10, D14	D7	0.72	1.28	19	D7, D11	D10	0.61	1.35
9	D10, D14	D11	0.70	1.73	20	D1, D10	D14	0.60	2.00
10	D9, D10	D7	0.70	1.26	21	D3, D7	D10	0.60	1.35
11	D3, D11	D10	0.68	1.52					

5. Analysis of PSC inspection data before and after COVID-19

Comparison between the average level from 2017 (or 2018) to 2019 and the level in 2020 in PSC inspection

Indicator	MoU	Tokyo MoU	Abuja MoU	Black Sea MoU	Caribbean MoU
Number of inspections	Average of 2017 to 2019	42,129	2,409	5,455	897
	2020	25,282	2,128	5,722	261
	2020 vs. average of 2017 to 2019	-39.99%	-11.66%	4.90%	-70.89%
Average number of deficiencies	Average of 2017 to 2019	2.821	0.296	4.800	\
	2020	2.222	0.553	3.238	\
	2020 vs. average of 2017 to 2019	-21.24%	86.79%	-32.55%	\
Detention rate	Average of 2017 to 2019	0.023	0.007	0.048	0.014
	2020	0.020	0.004	0.042	0.015
	2020 vs. average of 2017 to 2019	-13.76%	-41.26%	-12.22%	13.36%

Indicator	MoU	Indian MoU	Mediterranean MoU	Paris MoU	Riyadh MoU
Number of inspections	Average of 2017 (or 2018) to 2019	7,707	5,311	17,935	3,162
	2020	6,001	3,204	13,152	683
	2020 vs. average of 2017 (or 2018) to 2019	-22.13%	-39.67%	-26.67%	-78.40%
Average number of deficiencies	Average of 2017 (or 2018) to 2019	2.817	2.182	2.231	\
	2020	2.762	1.895	2.116	\
	2020 vs. average of 2017 (or 2018) to 2019	-1.96%	-13.19%	-5.14%	\
Detention rate	Average of 2017 (or 2018) to 2019	0.031	0.026	0.033	0.013
	2020	0.036	0.014	0.028	0.020
	2020 vs. average of 2017 (or 2018) to 2019	15.93%	-46.68%	-15.86%	58.04%

Yan R., Mo H., Guo X., Wang S., 2021. Is port state control in uenced by COVID-19? Evidence from inspection data. Submitted to Transport Policy, under first round revision (major revisions).

Comparison between the average level from 2017 (or 2018) to 2019 and the level in 2020 in PSC inspection

- The total number of inspections conducted in 2020 decreases remarkably compared to the average level from 2017 (or 2018) to 2019 in most MoUs by 12% to 78% as expected.
- The average number of deficiencies identified per inspection also decreases by 2% to 33% in most MoUs except Abuja MoU.
- The probability of detention per inspection is also reduced in 2020 in most MoUs by 12% to 47%.

Yan R., Mo H., Guo X., Wang S., 2021. Is port state control in uenced by COVID-19? Evidence from inspection data. Submitted to Transport Policy, under first round revision (major revisions).

Thank you!

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