THE HONG KONG POLYTECHNIC UNIVERSITY
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IDEAS Innovation-driven Education and Scholarship | Faculty of Business 工商管理學院

Department of LOGISTICS & MARITIME STUDIES 物流及航運學系

A Data-driven Global Port Performance Monitoring System: Models, Methods, and Applications

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15th Oct 2023

A real-time port monitoring system

- 1 Background and structure
- 2 Port congestion
- 3 Port productivity and throughput forecasting
- 4 Port connectivity
- 5 Port skipping identification (liner service disruption)
- 6 Vessel destination prediction

① Background and structure

AIS: GPS of ships, but with more information

Table 2. Attributes of AIS data.

Data field	Type	Description
AIS identity and location	Static	Maritime Mobile Service Identity (MMSI) and the location of the system's antenna on board
Ship identity	Static	Ship name, IMO number, type, and call sign of the ship
Ship size	Static	Length and width of the ship
Ship position	Dynamic	Latitude and longitude (up to 0.0001 min accuracy)
Speed	Dynamic	Ranging from 0 knot to 102 knots (0.1 knot resolution)
Rate of turn	Dynamic	Right or left (ranging from 0 to 720° per minute)
Navigation direction	Dynamic	Shipping course, heading, and bearing of the ship
Time stamp	Dynamic	Second field of the UTC time when the subject data packet was generated
Navigation status	Dynamic	Includes "at anchor," "under way using engine(s)," and "not under command"
Destination and ETA	Voyage-related	Destination port and the estimated time of arrival of the ship
Draught	Voyage-related	Ranges from 0.1 m to 25.5 m


Transport Reviews

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How big data enriches maritime research – a critical review of Automatic Identification System (AIS) data applications

Dong Yang, Lingxiao Wu, Shuaian Wang, Haiying Jia & Kevin X. Li

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Published online: 28 Jul 2019.

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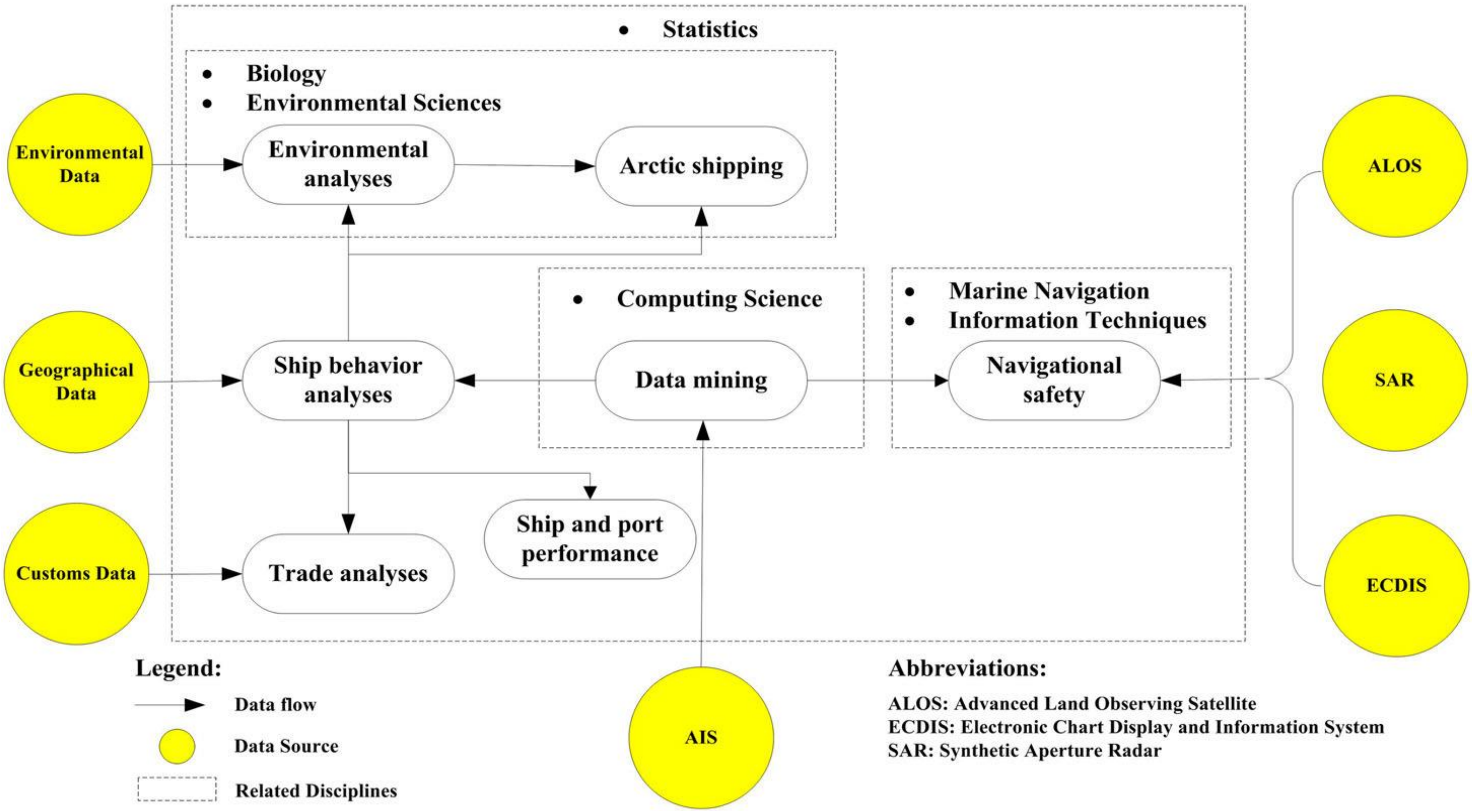
Relationship matrix of AIS studies



How to redefine port performance figures

- Over the last two years almost 90 percent of the data in the world was generated.
- Maritime statistics on a monthly or yearly frequency fails to reflect the rapid change in the economy.

Maritime statistics regarding port performance
- Low frequency
- Delayed
- Unavailable and insufficient
- Difficult to obtain

How can AIS be used to redefine port performance figures

?

Break the data barriers and promote global port statistics standardization.

Enhance port management, promote digitization in the maritime industry, and facilitate regional economic development.

1 Background and structure

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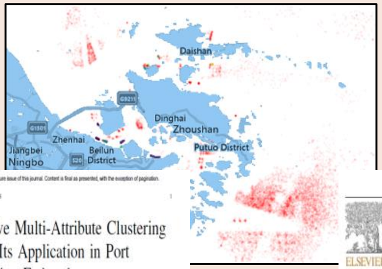
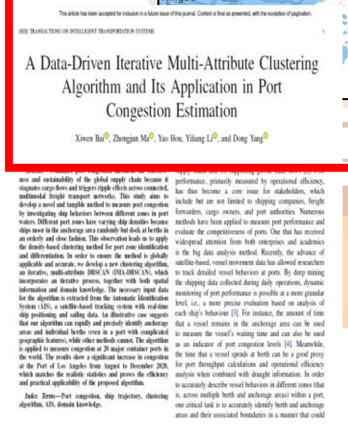
Real-time port performance monitoring & Real-time event analysis

Port Congestion

- Proposed two congestion indicators: delay ratio and delay time
- Represents the efficiency of a port




A Data-Driven Iterative Multi-Attribute Clustering Algorithm and Its Application in Port Congestion Estimation

Xiwen Bai, Zhongjun Ma, Yao Hou, Yilang Li, and Dong Yang

Port Productivity

- Port throughput calculation based on berthing time and Port handling efficiency
- Represents output of a port

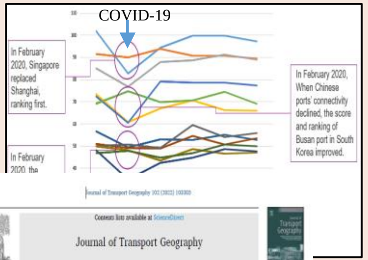

Transportation Research Part E

Towards sustainable port management: Data-driven global container ports turnover rate assessment

Dong Yang, Shiguan Liao, Y.H Venus Lun, Xiwen Bai

Port Connectivity

- Proposed a holistic AIS-based port connectivity measurement system
- Measures connectivity of a port without external data



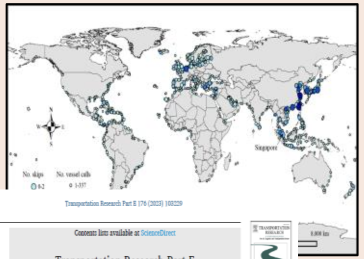

Journal of Transport Geography

Does the traffic volume of a port determine connectivity? Revisiting port

Xiwen Bai, Liangqi Cheng, Dong Yang, Ouchen Cai

Port-Skipping identification

- Proposed a data-driven framework to identify port-skipping
- Reveal specific strategic decisions to heal service disruptions




Transportation Research Part E

How liner shipping heals schedule disruption: A data-driven framework to uncover the strategic behavior of port-skipping

Lingye Zhang, Dong Yang, Xiwen Bai, Kee-hung Lai

Vessel destination prediction

- Proposed a stacking model for vessel destination prediction
- To predict the destination of a VLCC from a fixed origin


Transportation Research Part C

Vessel destination prediction: A stacking approach

Zechen Yin, Dong Yang, Xiwen Bai

A global port performance monitoring system


COVID-19: What we do

Home | What We Do | Where We Work | Get Involved | News & Library | About

« All Events

This event has passed.

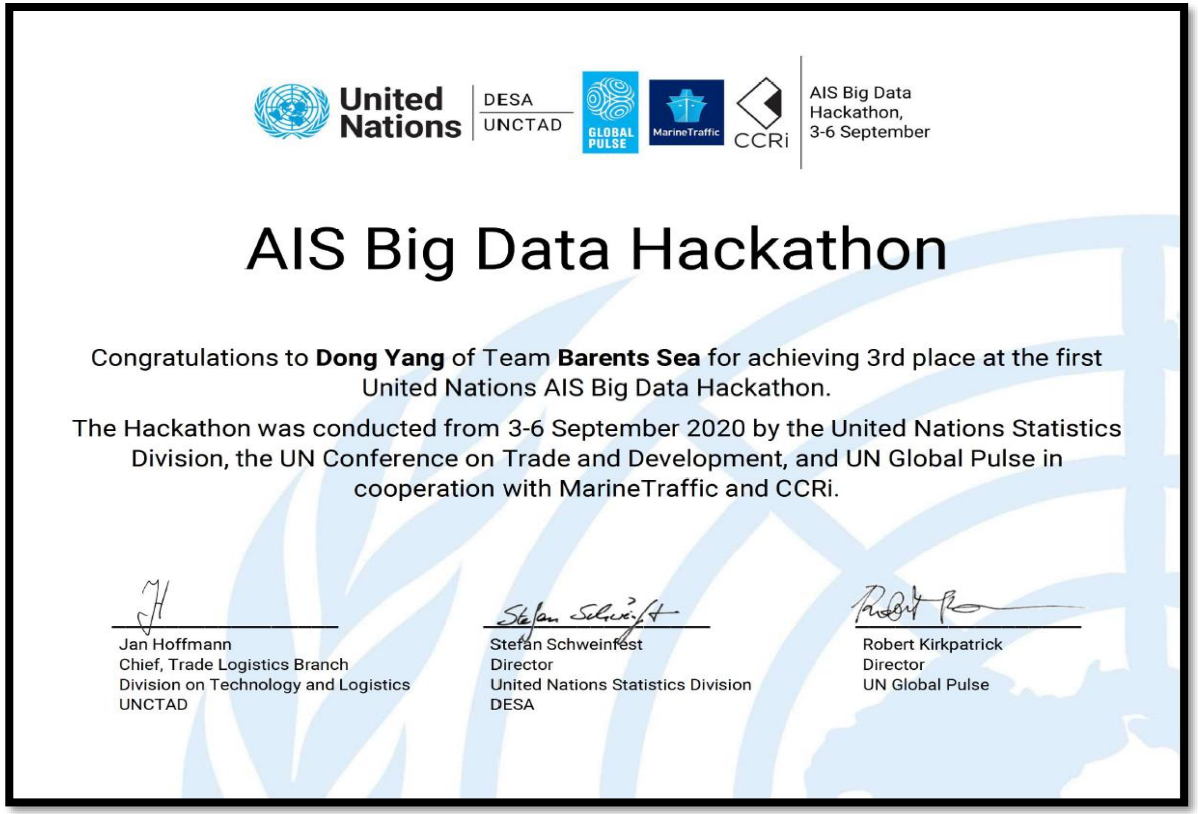
AIS Big Data Hackathon

3 September, 2020 at 8:00 AM - 6 September, 2020 at 5:00 PM EDT

United Nations | DESA | UNCTAD | GLOBAL PULSE | MarineTraffic | AIS Big Data Hackathon, 3-6 September

The United Nations Statistics Division, the United Nations Conference on Trade and Development, and UN Global Pulse are jointly, in collaboration with MarineTraffic and consultation with AIS Task Team members, organizing a remote participation Hackathon from 3-6 September. The Hackathon is calling on teams to explore the use of Automatic Identification System (AIS) data to inform COVID-19 response and to assist the world in its fight against climate change.

2020 UN Hackathon Competition Third Place


United Nations | DESA | UNCTAD | GLOBAL PULSE | MarineTraffic | CCRi | AIS Big Data Hackathon, 3-6 September

AIS Big Data Hackathon

Congratulations to **Dong Yang** of Team **Barents Sea** for achieving 3rd place at the first United Nations AIS Big Data Hackathon.

The Hackathon was conducted from 3-6 September 2020 by the United Nations Statistics Division, the UN Conference on Trade and Development, and UN Global Pulse in cooperation with MarineTraffic and CCRi.

Jan Hoffmann
Chief, Trade Logistics Branch
Division on Technology and Logistics
UNCTAD

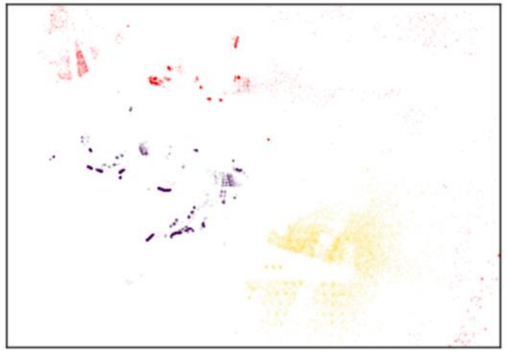
Stefan Schweinfest
Director
United Nations Statistics Division
DESA

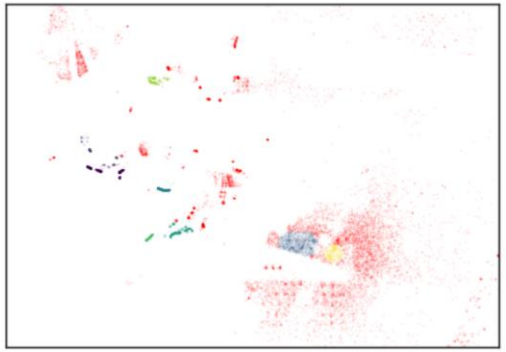
Robert Kirkpatrick
Director
UN Global Pulse

An illustrative case

The radius is too large to identify the anchorages

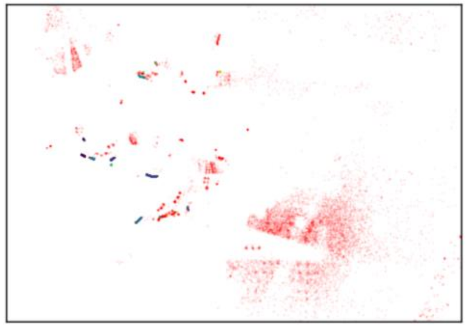
First Iteration





Second Iteration

Reduce the radius, identify anchorages (red dots) and berths (other colors), but some points are still misidentified (blue/yellow)

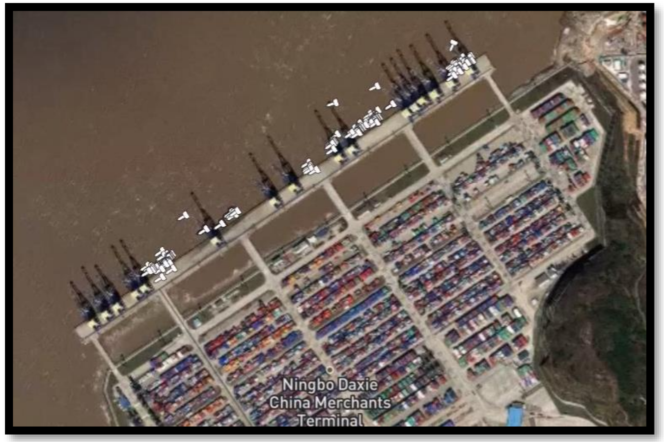


Third Iteration

Continue to reduce the radius and identify the anchorages (red dots) and berths (other colors)

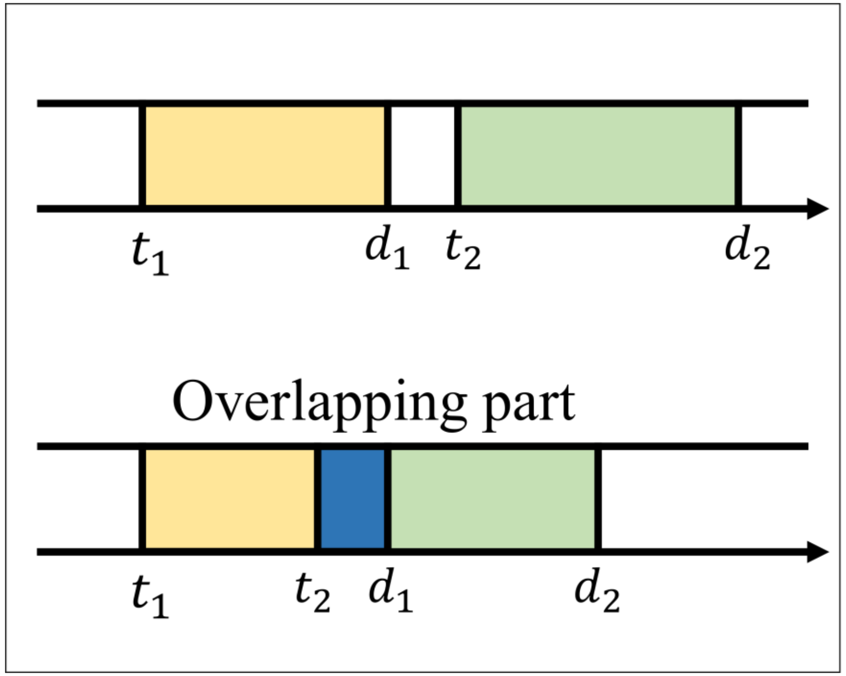
- The ship densities are different in berth and anchorage area.
- Ship arrive the anchorage first and then berth
- Ships' heading direction are different

Should we set different parameter in different ports? iteration.



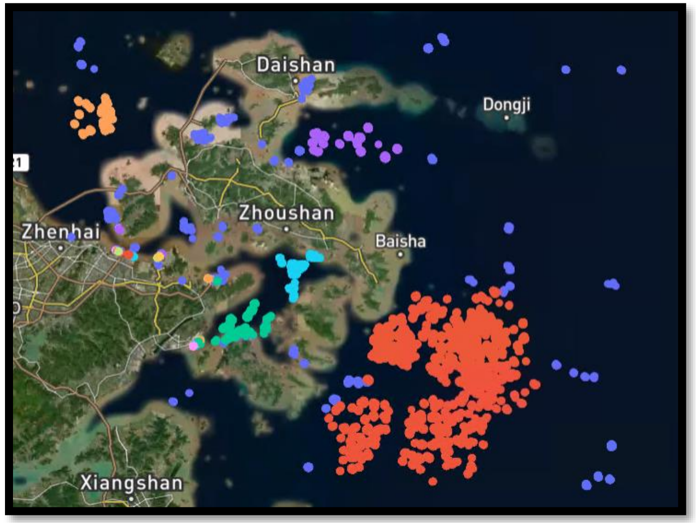
Heading when the ship is at berth

Heading when the ship is at anchorage



Determining whether merging is possible

The berths and anchorages



The result of IMA-DBSCAN

Terminal Daxie

Terminal Yuandong

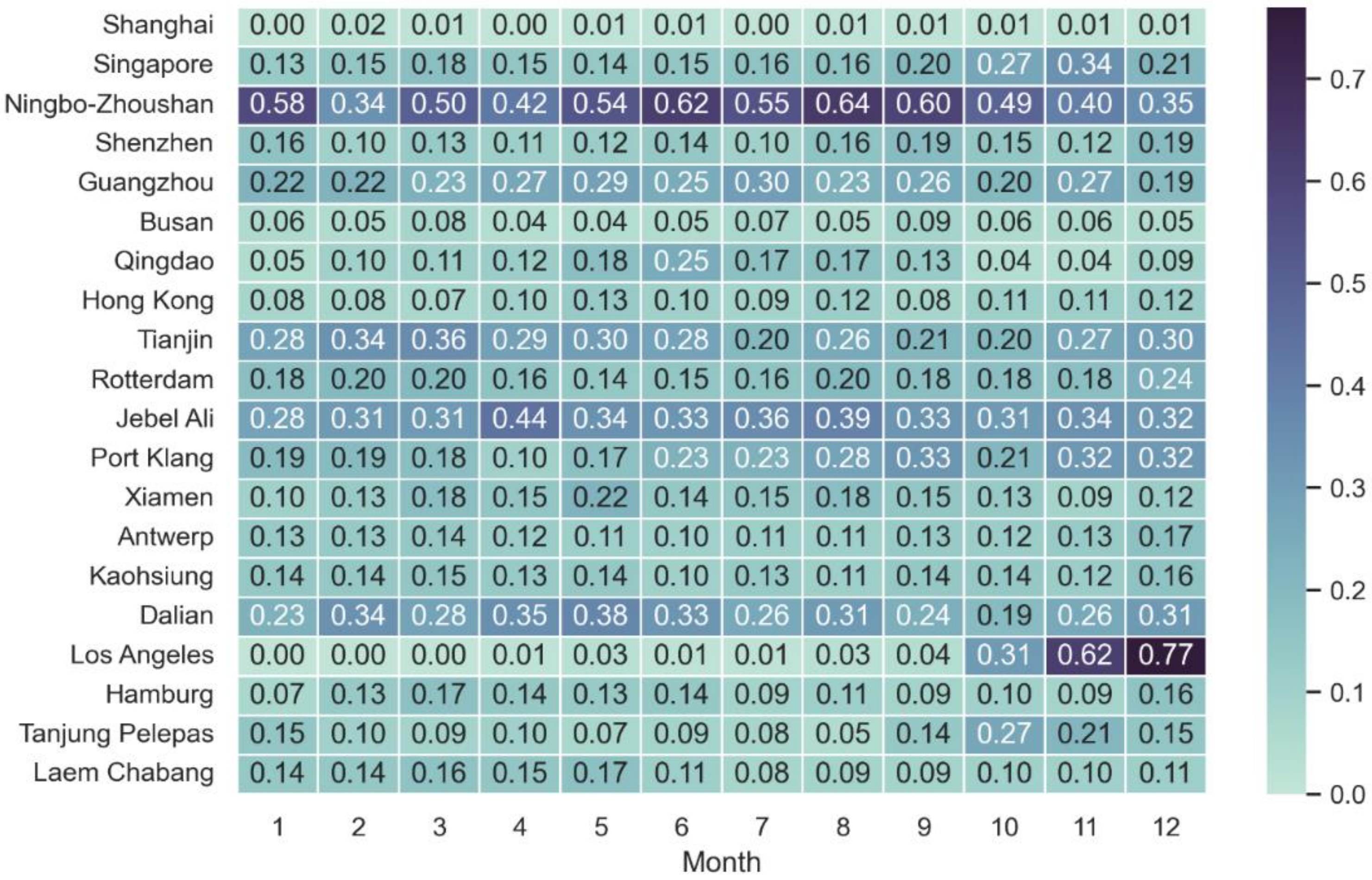
2 Port Congestion Estimation

Port \ Month	1	2	3	4	5	6	7	8	9	10	11	12
Shanghai	0.07	0.27	0.02	0.03	0.17	0.07	0.00	0.04	0.31	0.33	0.07	0.21
Singapore	2.16	2.24	3.48	3.29	2.90	2.94	2.72	2.79	4.41	7.64	10.91	4.50
Ningbo-Zhoushan	19.49	9.64	14.94	11.20	13.97	20.11	17.07	24.47	22.36	16.34	10.20	9.46
Shenzhen	2.96	2.33	2.01	1.73	2.07	2.27	1.63	2.75	3.75	3.15	2.39	3.49
Guangzhou	5.54	9.17	5.04	7.73	6.99	6.91	7.99	5.19	6.48	5.05	6.35	4.27
Busan	1.89	1.53	2.00	1.34	1.57	1.35	1.43	1.45	2.84	1.26	1.59	0.99
Qingdao	1.26	3.69	2.82	3.85	7.26	7.39	3.91	4.78	2.80	1.01	0.85	2.19
Hong Kong	1.78	3.64	1.81	3.13	3.05	2.05	2.18	2.69	1.62	2.01	2.27	2.15
Tianjin	7.51	16.12	12.29	6.83	9.09	7.46	3.85	6.39	5.09	4.26	7.47	7.52
Rotterdam	5.22	7.23	5.72	4.90	2.94	2.82	3.37	4.48	5.03	5.73	3.94	7.18
Jebel Ali	5.68	6.04	6.97	10.47	9.59	7.53	10.55	10.76	7.09	7.44	7.62	6.59
Port Klang	3.40	2.84	2.61	1.18	4.55	4.49	4.58	6.38	7.44	3.77	8.75	11.92
Xiamen	1.75	5.81	4.26	4.21	6.28	4.19	3.45	3.15	2.70	2.06	1.89	2.37
Antwerp	2.78	1.93	1.91	2.49	1.96	1.83	1.45	1.61	2.94	1.79	2.08	4.67
Kaohsiung	2.91	4.30	3.01	2.55	2.78	1.62	2.48	2.17	2.81	2.92	1.88	4.28
Dalian	4.66	13.52	5.35	7.72	10.14	8.10	5.98	6.16	5.20	3.70	6.16	13.95
Los Angeles	0.00	0.00	0.00	0.32	0.47	0.30	0.28	0.51	1.58	13.55	42.63	80.53
Hamburg	2.37	2.80	4.09	4.33	3.62	2.99	2.04	1.92	1.60	1.87	2.29	3.83
Tanjung Pelepas	3.26	2.31	2.27	1.67	2.16	1.62	1.16	0.78	3.01	7.94	5.76	3.36
Laem Chabang	2.21	3.81	2.37	2.30	2.47	1.36	0.98	1.04	1.23	1.28	3.12	1.71

Month

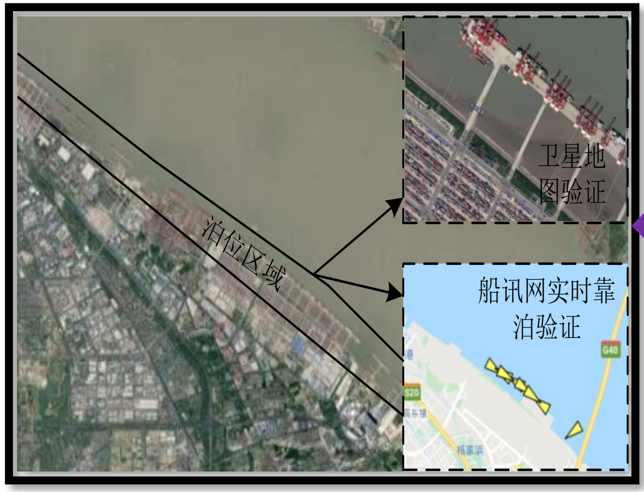
The Average Congestion Time (ACT) of top 20 container ports in 2020

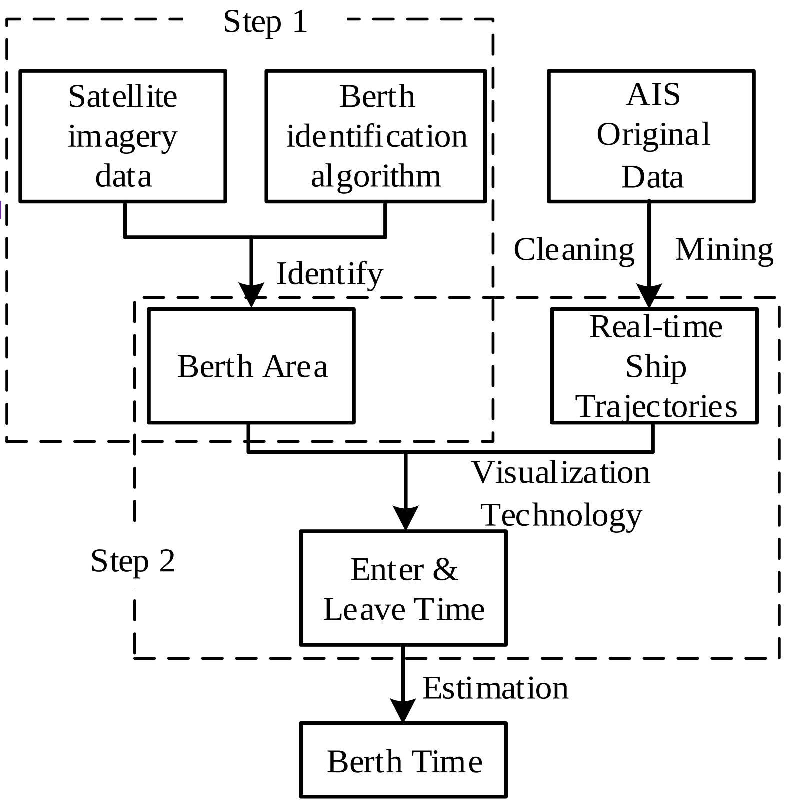
2 Port Congestion Estimation

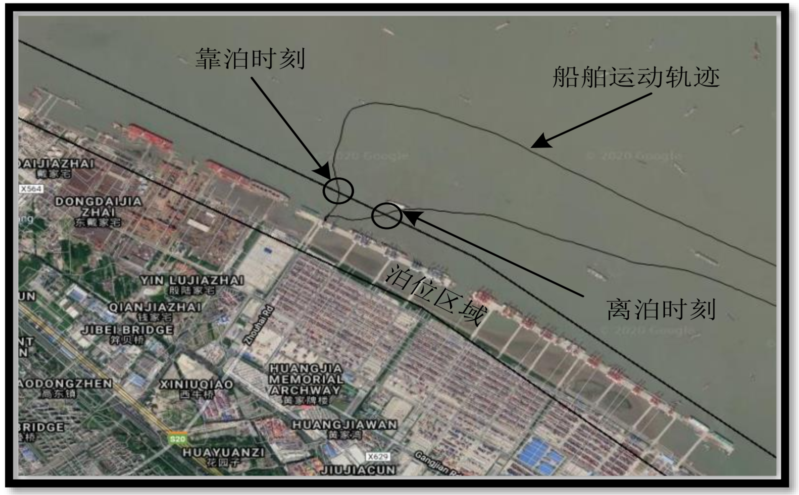


The Average Congestion Rate (ACR) of top 20 container ports in 2020

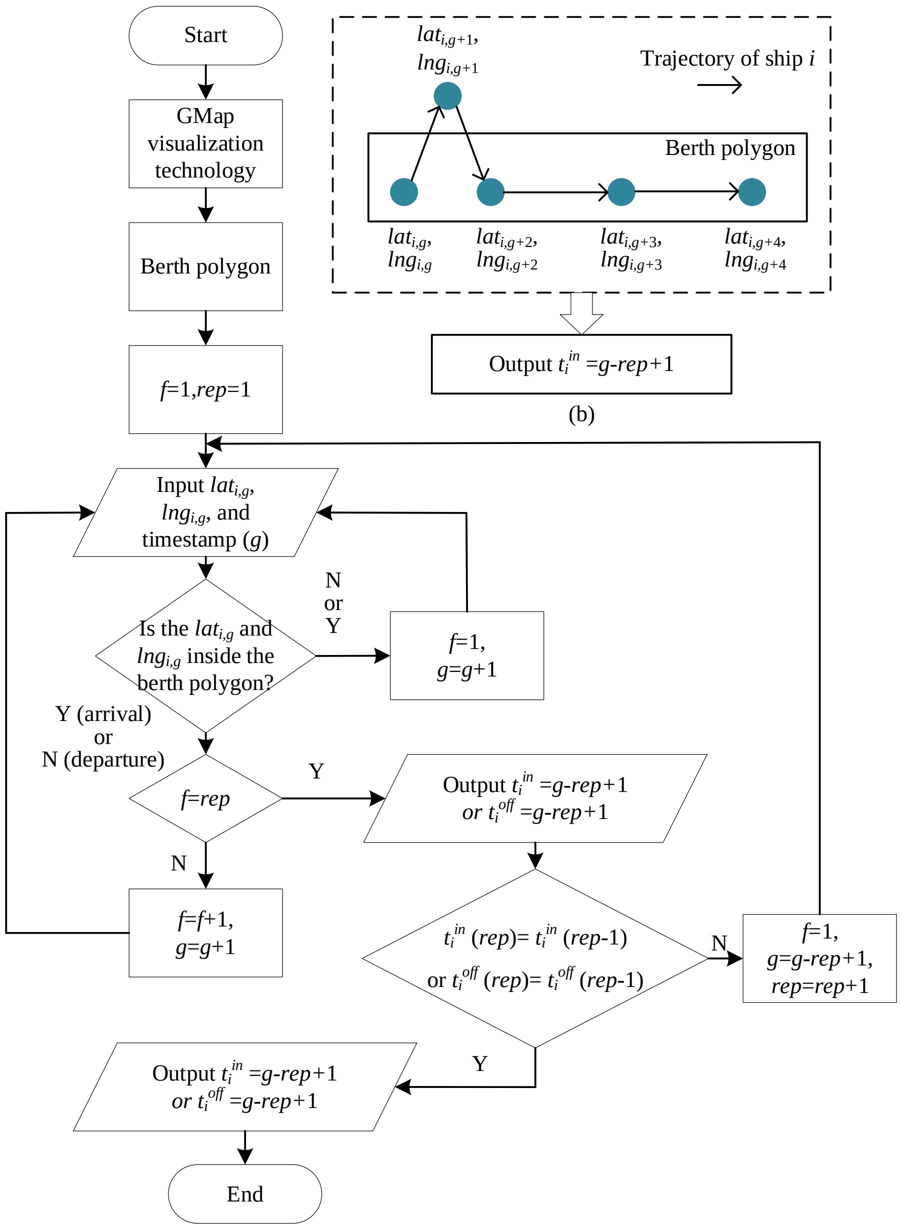
Port productivity estimation







Port productivity estimation



(a)

Port productivity estimation

Efficiency

$$e^{o}_{k,l} = \frac{Q_{k,l}}{\sum_{n \in N} \sum_{i \in n} w_n t_i^{berthing}}$$

Throughput

Turnover rate

Ship weight parameter

Port productivity estimation

(a) Port of Shanghai

(b) Port of Singapore

(e) Port of Busan

(f) Port of Hong Kong

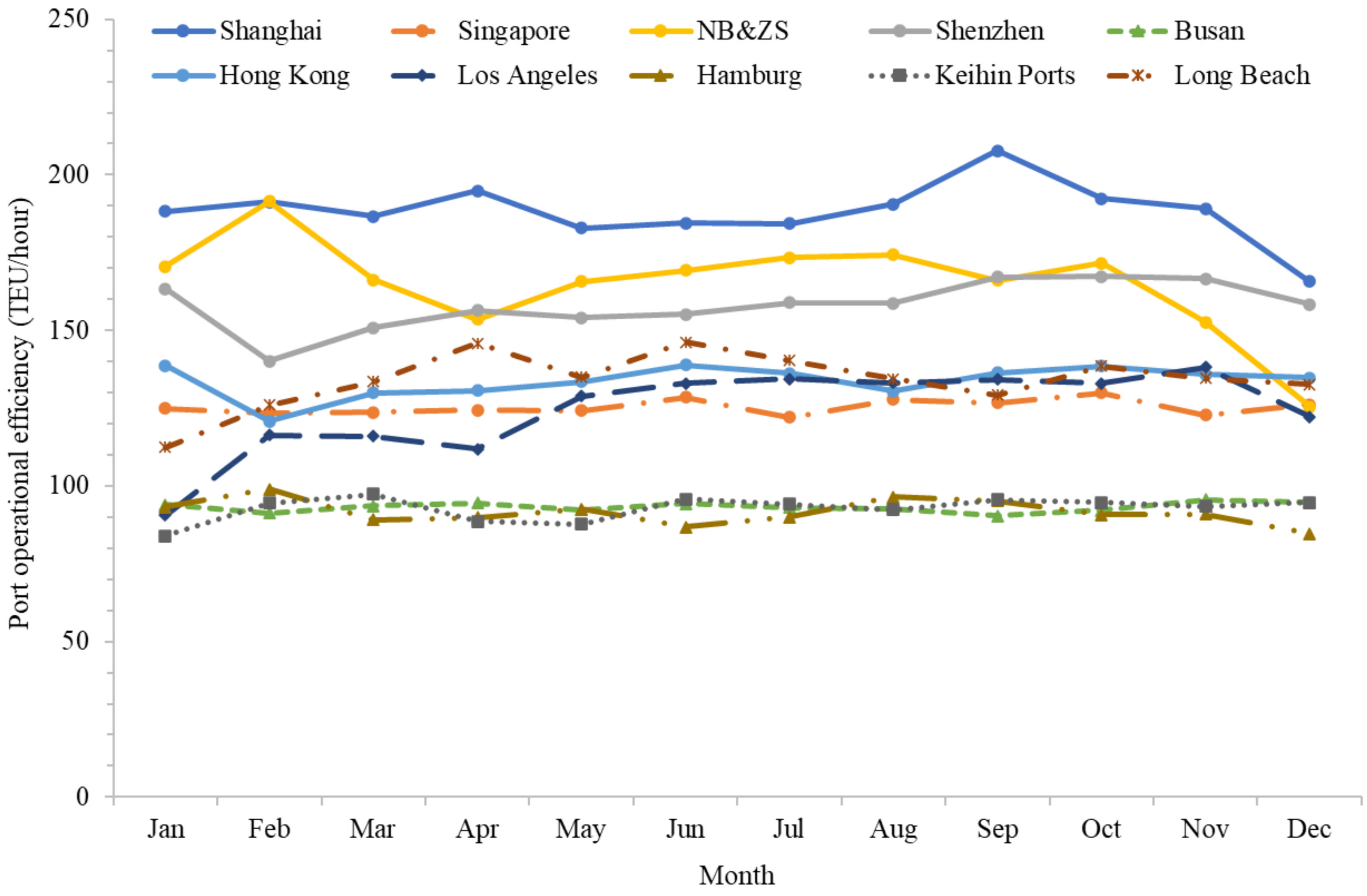
(c) Port of NB&ZS

(d) Port of Shenzhen

(g) Port of Hamburg

(h) Port of Los Angeles

Port efficiency of during COVID-19



Port throughput estimation

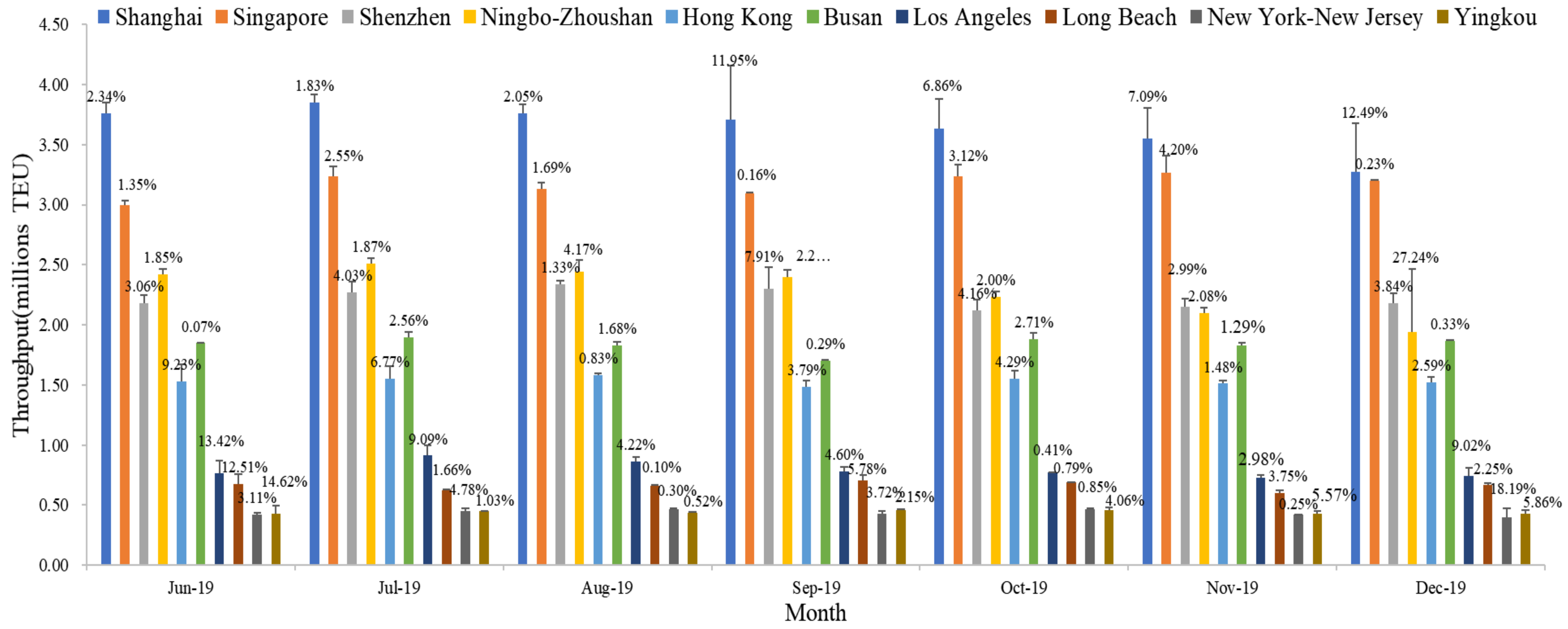
The idea of **moving average** (**MA**) is used to future productivity of port

The mean absolute percentage error (MAPE), also known as mean absolute percentage deviation (MAPD), is used to measure the prediction accuracy .
It usually expresses the accuracy as a ratio defined by the formula:

$$\mathrm{MAPE} = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|$$

where A_t is the actual value and F_t is the forecast value. The MAPE is also sometimes reported as a percentage, which is the above equation multiplied by 100. The difference between A_t and F_t is divided by the actual value A_t again. The absolute value in this calculation is summed for every forecasted point in time and divided by the number of fitted points n.

Port throughput estimation accuracy



MA(Month=5)	Shanghai	Singapore	Shenzhen	Ningbo-Zhoushan	Hong Kong	Busan	Los Angeles	Long Beach	New York-New Jersey	Yingkou	Average
MAPE	6.37%	1.90%	3.90%	5.93%	4.14%	1.28%	6.25%	3.83%	4.46%	4.83%	4.29%

Port connectivity estimation

Research Gap

Categories	References
Port-perspective indicators	
Liner services	LSCI, PCI
Ship calls	LSCI, Jia et al. (2017)
Capacity/Cargo loads	LSCI, Wang et al. (2016), Jia et al. (2017)
Liner companies	LSCI
Connected countries/regions	LSCI, PCI
Maximum vessel	LSCI, Jia et al. (2017)
Network-perspective indicators	
Influence	Jiang et al. (2015)
Distance	Wang et al. (2016)
Accessibility	Low et al. (2009), Tovar et al. (2015)

- **Industry index mainly focus on indicators relating to port only;**
- **Academic papers discuss the network indicators, but difficult in calculation and only cover regions (due to data richness);**
- **Low frequency and delay publication.**

Port connectivity estimation

Methodology

1.Vessel Visits
The scale of liner services serving a port
港口访问

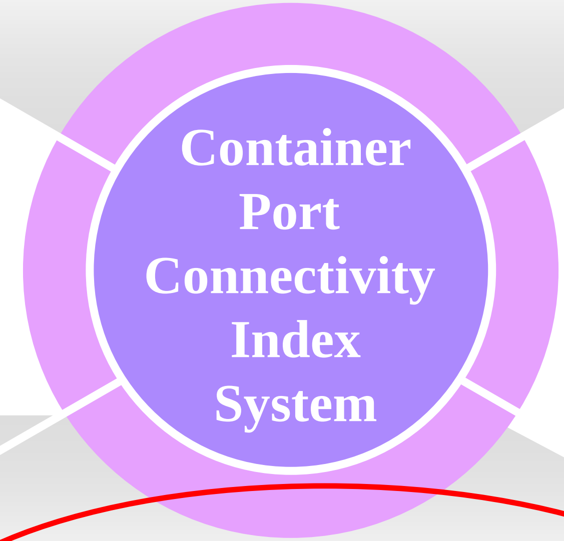
2.Connected Countries
The accessibility of a port through liner services
班轮服务数量

3.Strategic importance
The frequency of intercontinental long-distance transportation
洲际远洋运输

4.Degree Centrality
Represent the frequency of trade exchange for imports and exports

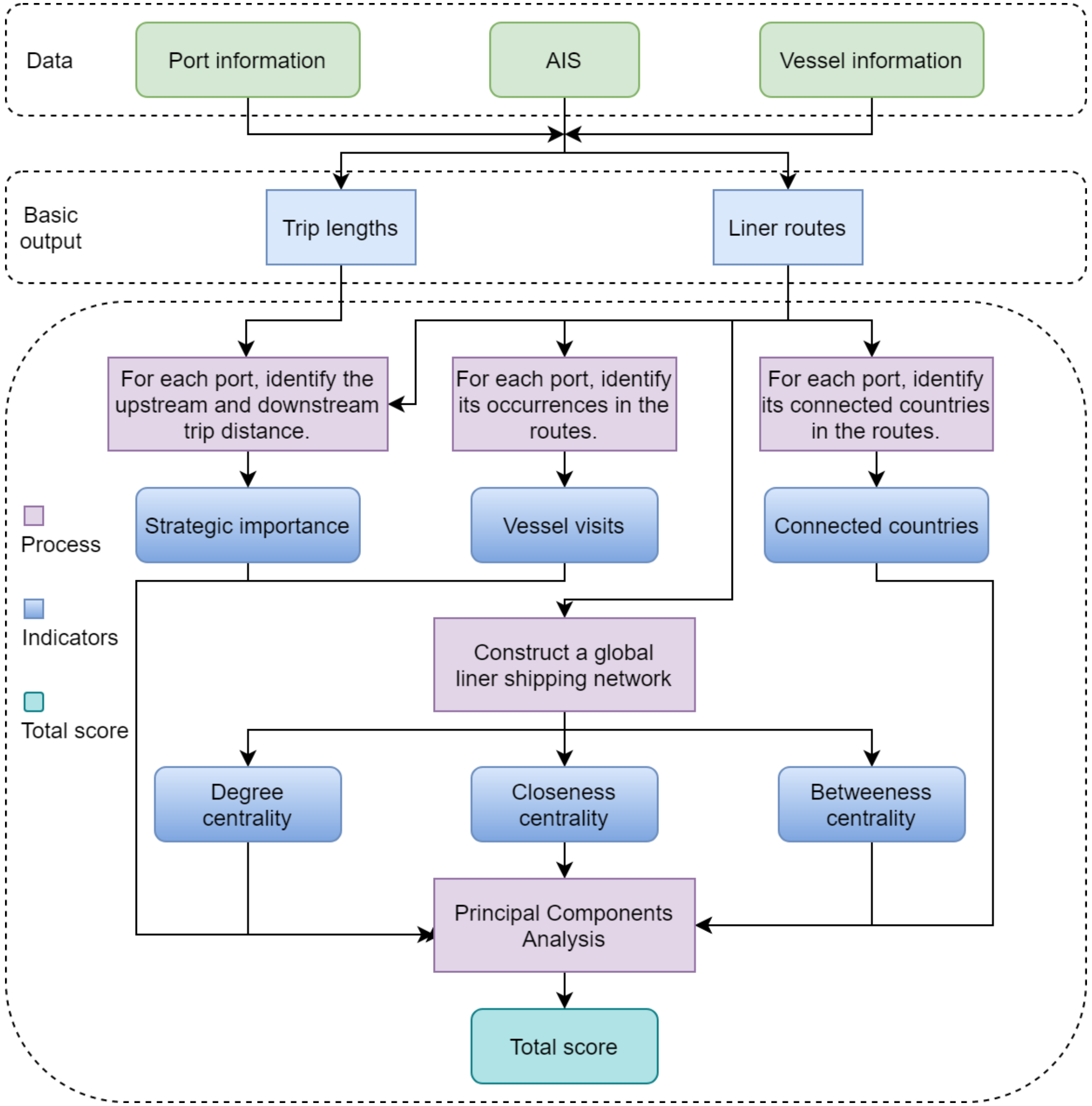
5.Closeness Centrality
Represent the convenience to reach other ports

6.Betweenness Centrality
Represent the relative importance to lie in any truck line
网络性指标



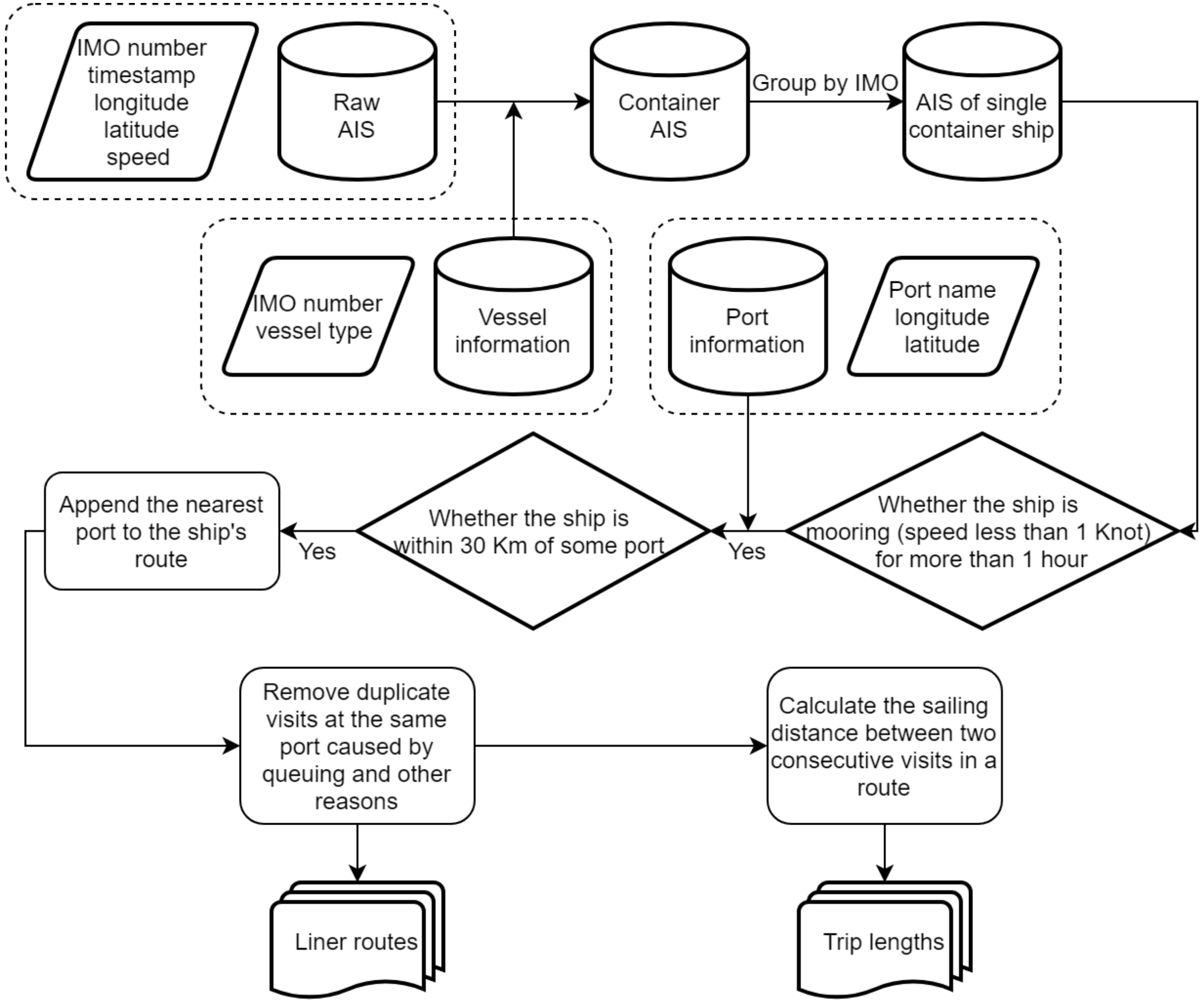
Port connectivity estimation

Methodology



Port connectivity estimation

Methodology



Some preliminary result

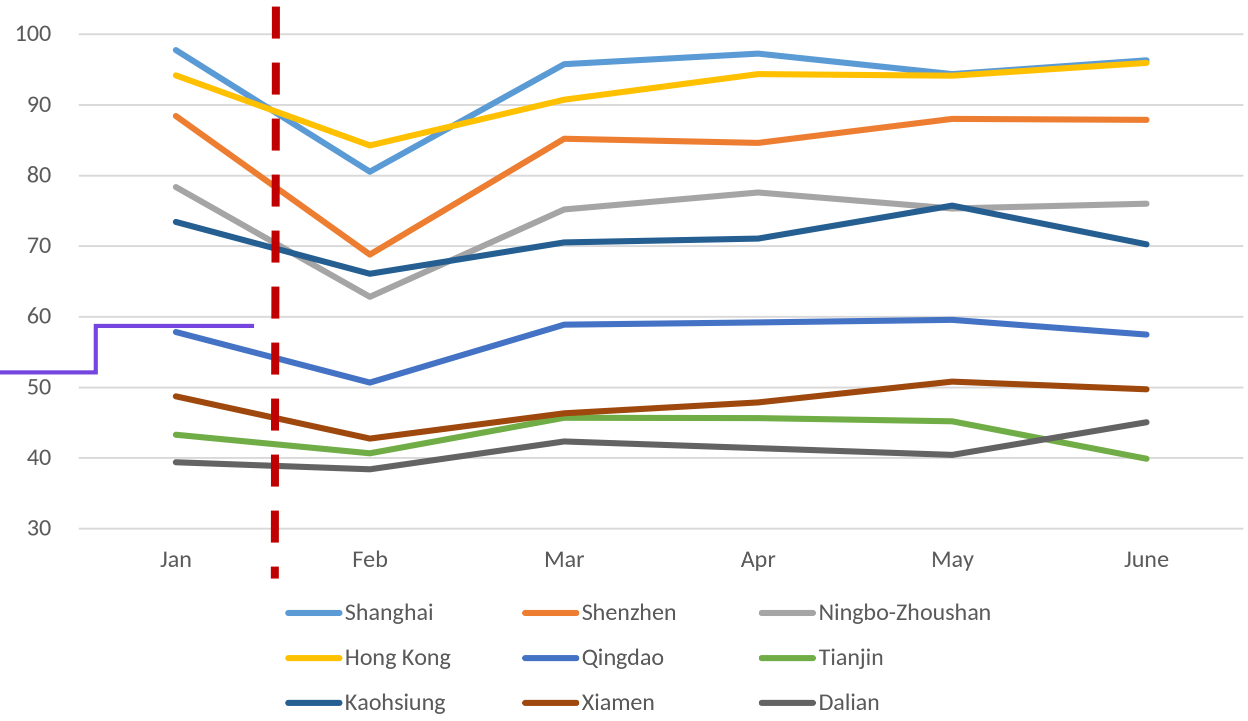
Port	Vessel Visits	Connected Countries	Degree Centrality	Betweenness Centrality	Closeness Centrality	Strategic Importance
Shanghai, China	1206	56	0.0612	0.0709	0.3344	4.4502
Singapore	1327	80	0.0633	0.0535	0.3676	4.2433
Shenzhen, China	950	67	0.0496	0.0677	0.2608	4.0067
Ningbo-Zhoushan, China	868	53	0.0426	0.0477	0.3482	4.4332
Busan, South Korea	697	28	0.0362	0.0796	0.1696	4.4233
Hong Kong, S.A.R, China	1073	54	0.056	0.0824	0.2339	4.0629
Qingdao, China	528	33	0.0272	0.0368	0.3271	4.1238
Tianjin, China	281	22	0.0137	0.0218	0.2889	4.2404
Jebel Ali, Dubai, United Arab Emirates	366	55	0.0177	0.0112	0.3018	4.1025
Rotterdam, The Netherlands	550	61	0.0289	0.0399	0.2024	4.2863
Port Klang, Malaysia	628	56	0.0316	0.0325	0.3277	4.2126
Antwerp, Belgium	390	75	0.0197	0.0191	0.3747	4.4863
Kaohsiung, Taiwan, China	704	41	0.0362	0.0583	0.2567	4.4121
Xiamen, China	301	27	0.0161	0.0313	0.2659	4.3469
Dalian, China	213	19	0.0109	0.0227	0.2342	3.9768
Los Angeles, U.S.A	86	19	0.0035	0.0018	0.5919	4.206
Tanjung Pelepas, Malaysia	415	61	0.0209	0.0205	0.3531	4.7835
Hamburg, Germany	286	53	0.0151	0.0222	0.2721	4.4747
Long Beach, U.S.A.	76	26	0.0032	0.0021	0.4858	4.5753
Keihin Ports, Japan	462	31	0.0229	0.0354	0.2855	4.0922
Tanjung Priok, Jakarta, Indonesia	311	26	0.0149	0.0118	0.3868	4.1365
New York-New Jersey, U.S.A.	162	50	0.0076	0.0064	0.5103	4.0552
Colombo, Sri Lanka	317	46	0.0147	0.0056	0.455	4.0416
Ho Chi Minh City, Vietnam	415	20	0.0214	0.0314	0.3044	4.1107
Bremen/Bremerhaven, Germany	216	49	0.0109	0.017	0.2519	4.4909
Hanshin Port, Japan	406	23	0.0214	0.0389	0.2193	4.2438
Manila, Philippines	212	16	0.0105	0.012	0.3366	4.045

Some preliminary result

Results

Chinese ports

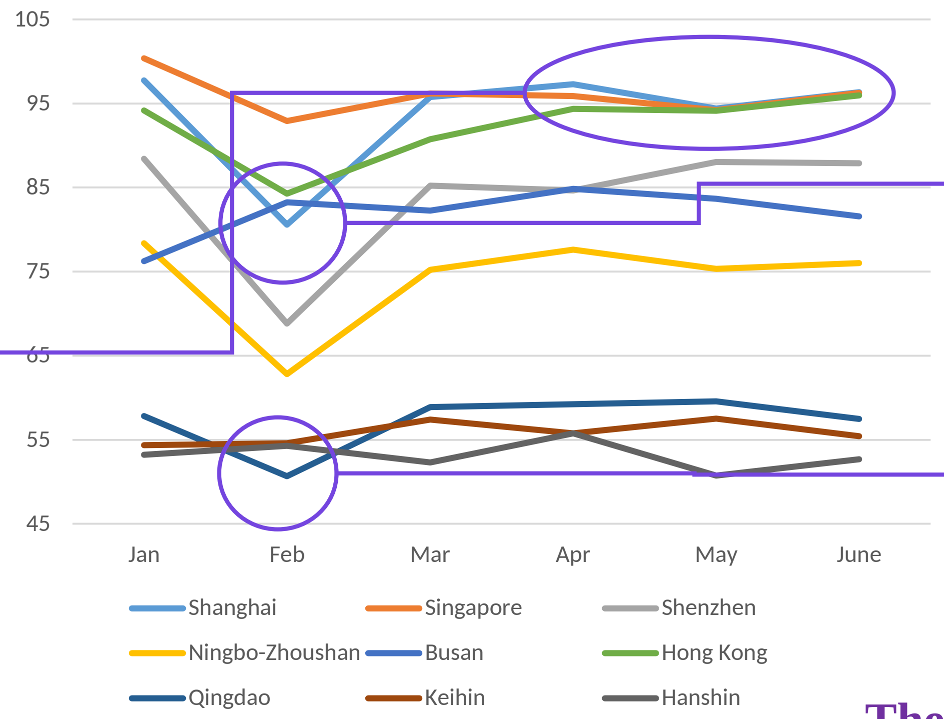
In February 2020, the Port Connectivity Index of Chinese ports declined significantly, and recovered from March.



4 Port connectivity estimation

Results

Top ports in Asia



Singapore ranked the first place in the first three months until Shanghai recovered in the next three months

Busan exceeded Shanghai, Shenzhen, and Ningbo-Zhoushan in February

Keihin and Hanshin exceeded Qingdao in February

The network centrality or strategic importance of these ports increased

Background

Although approximately 90% of the global trade is served by sea, various disruptive events may negatively interrupt the operation in liner shipping, including natural disasters, pandemics, political instability, terrorism, and inclement weather. Especially in recent years, there are rising concerns of uncertainties in global maritime logistics in the post COVID-19 era.

Widely adopted schedule recovery strategies:

- Adjusting the shipping speed (Speeding-up)
- Swapping the order of ports of call （Swapping）
- Skipping a port on the scheduled route （Port-skipping）

Data

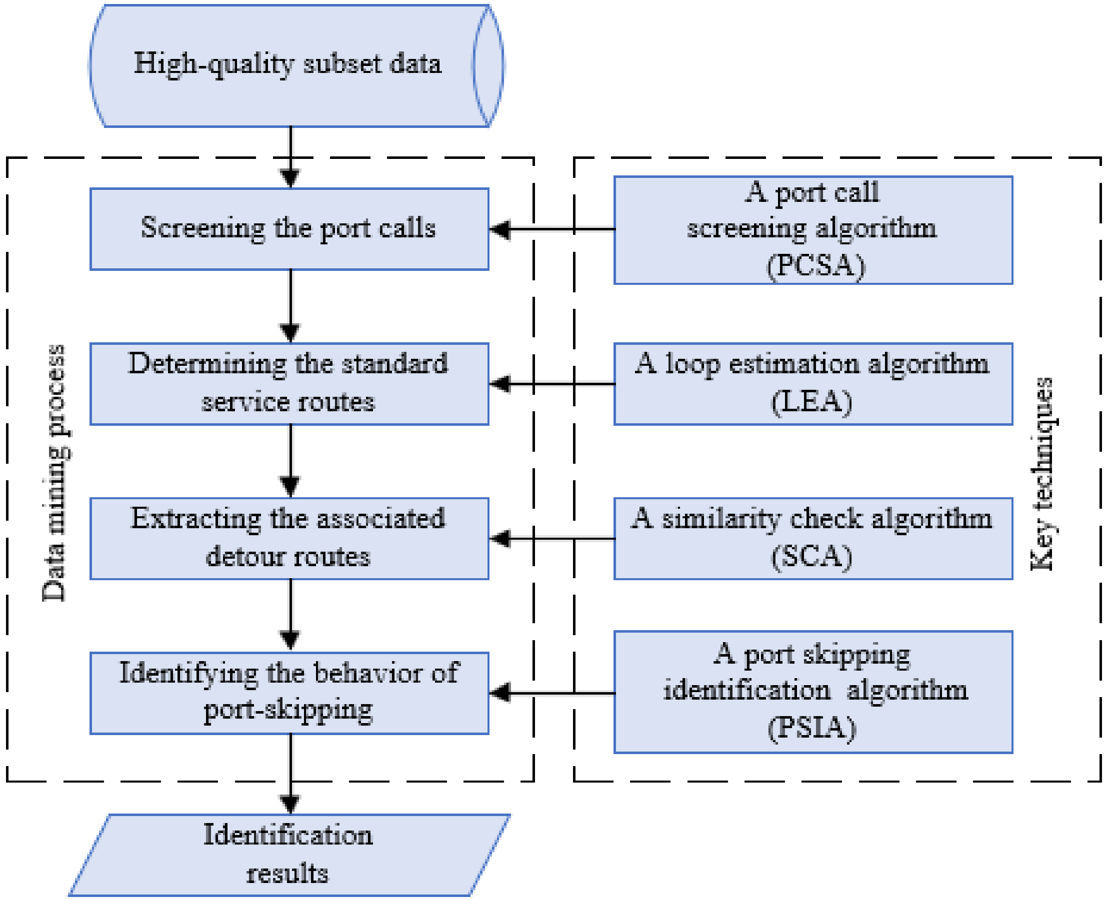
The experimental data in this study is the AIS data of container vessels from January 2016 to December 2020.

Before identifying the behavior of port-skipping, high-quality trajectory-related subset data needs to be extracted from the raw AIS data. After cleaning the raw data, the total number of the observed vessels is 1,936 and the data size is around 13.2 G containing over 232.7 million trajectory records.

Table 2. Descriptive statistics of the subset AIS data.

Parameter	Mean	Median	S.D.	Min	Max
Capacity (TEU)	1,758	1,421	1,207	194	13,574
Duration (month)	26	24	15	12	60
Trajectory record	120,234	108,185	60,835	7,004	343,969

Methodology



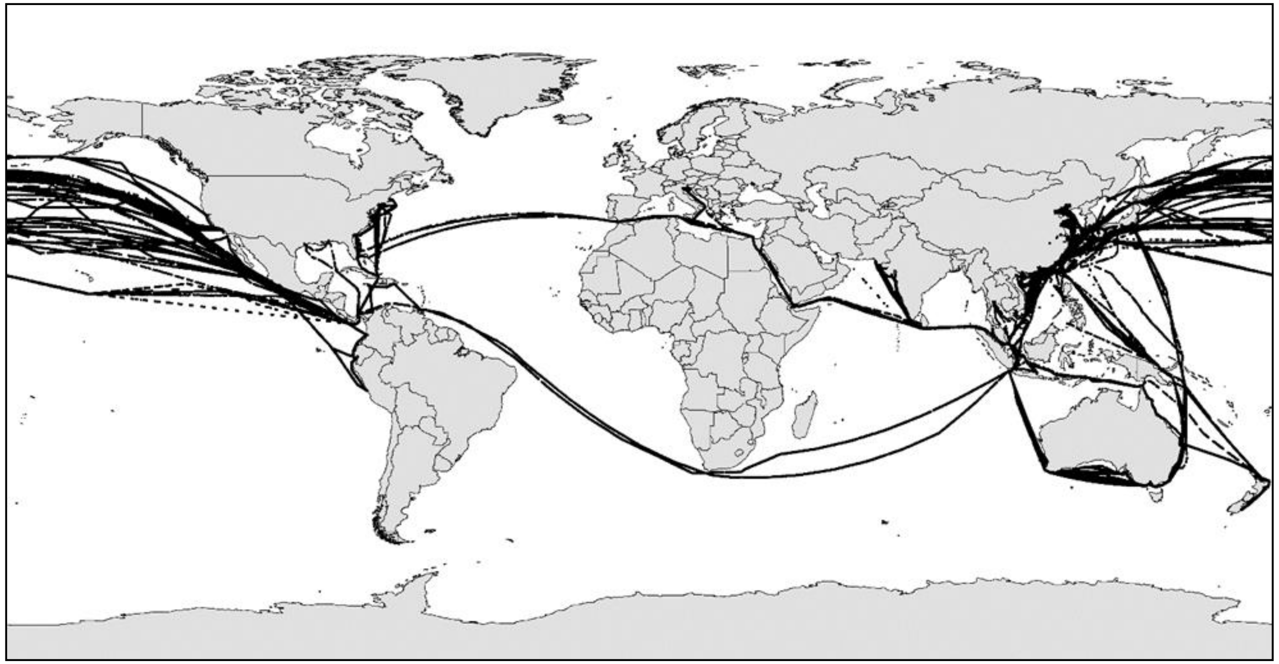
The overall framework for port-skipping identification based on data mining algorithms

A **four-step** data-driven framework is devised to identify the behavior of port-skipping, each supported by an independent data mining algorithm.

- **The first step** is to screen port calls of the observed vessels.
- **The second step** is to determine the standard service route (SSR) for each observed vessel.
- **The third step** is to measure the similarity between the SSR and the other loops.
- **The fourth step** is to identify port-skipping behavior.

Applications

The overall identification results



The identified routes of the observed vessels belonging to COSCO SHIPPING Lines.

Taking **COSCO SHIPPING Lines**, for example, **53 vessels** are included in the observed vessels, belonging to this world-leading liner shipping company. The identified routes for these vessels are shown in the left figure, which cover around **92%** of ports along the service routes published on the company's website (https://lines.coscoshipping.com/home/Services/route).

Applications

The overall identification results

The port-skipping status of the top-ranked ports.

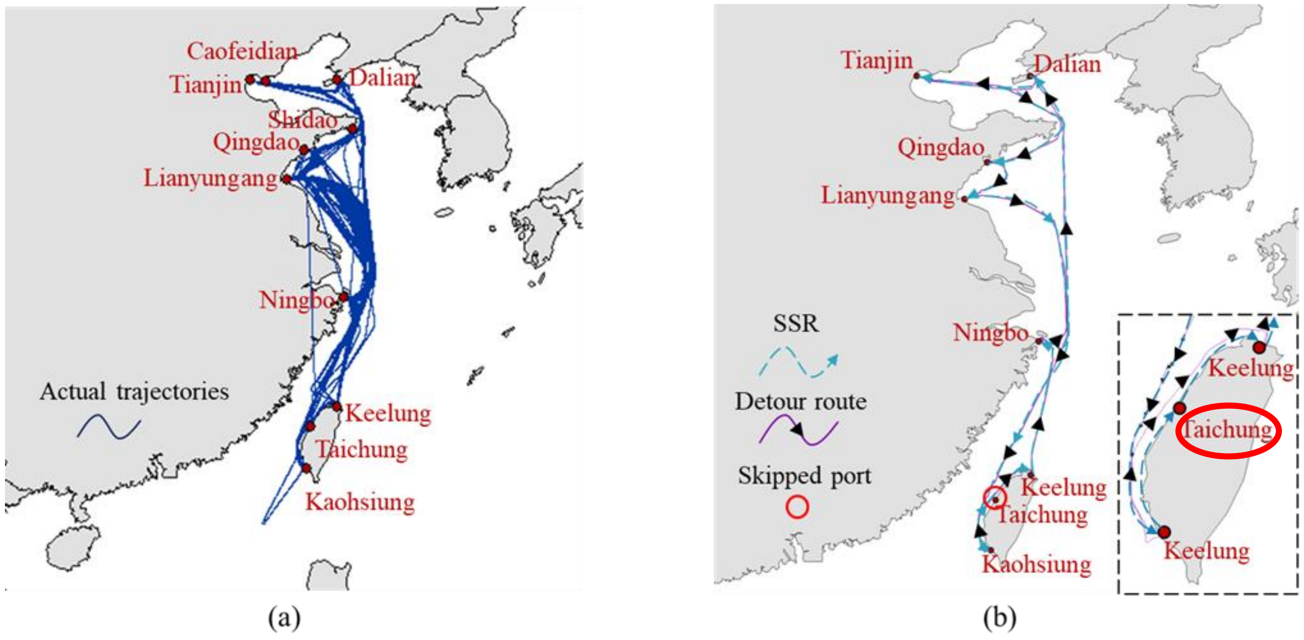
Port	No.	Ranking	Skip ratio	Port	No.	Ranking	Skip ratio
Charleston	1	76	4.17%	Balboa	24	53	0.31%
Melbourne	2	71	3.57%	Shanghai	25	1	0.30%
Taichung	3	94	1.57%	Colombo	26	23	0.29%
Rizhao	4	35	1.08%	Guayaquil	27	84	0.28%
Port Said	5	43	0.99%	Xiamen	28	13	0.27%
Nagoya	6	77	0.97%	Lianyungang	29	36	0.25%
Qingdao	7	6	0.94%	Tianjin	30	8	0.23%
Taipei	8	88	0.85%	Piraeus	31	33	0.23%
Felixstowe	9	49	0.84%	Hong Kong	32	9	0.18%
Tanjung Pelepas	10	15	0.84%	Kaohsiung	33	17	0.16%
Le Havre	11	68	0.66%	Incheon	34	60	0.15%
Yokohama	12	72	0.52%	Shenzhen	35	4	0.14%
Mersin	13	87	0.51%	Barcelona	36	54	0.11%
Tanjung Priok	14	26	0.45%	Yantai	37	52	0.10%
Bremerhaven	15	37	0.45%	Rotterdam	38	10	0.09%
Kobe	16	73	0.40%	Ambarli	39	70	0.09%
Tanger Med	17	24	0.40%	Singapore	40	2	0.09%
Algeciras	18	42	0.40%	Hai Phong	41	28	0.08%
Osaka	19	82	0.39%	Hamburg	42	20	0.07%
Gwangyang	20	85	0.38%	Port Klang	43	12	0.07%
Tokyo	21	46	0.35%	Antwerp	44	14	0.05%
Busan	22	7	0.34%	Laem Chabang	45	21	0.05%
Ningbo	23	3	0.32%	Ho Chi Minh	46	22	0.03%

The ports in the former half generally have a larger skip ratio and lower ranking than those in the latter half, most of which are regional shipping hubs or even global shipping hubs (such as Shanghai, Hong Kong, Singapore, Rotterdam, and Antwerp).

Applications

Schedule recovery scenario analysis

Case 1: Ordinary port-skipping

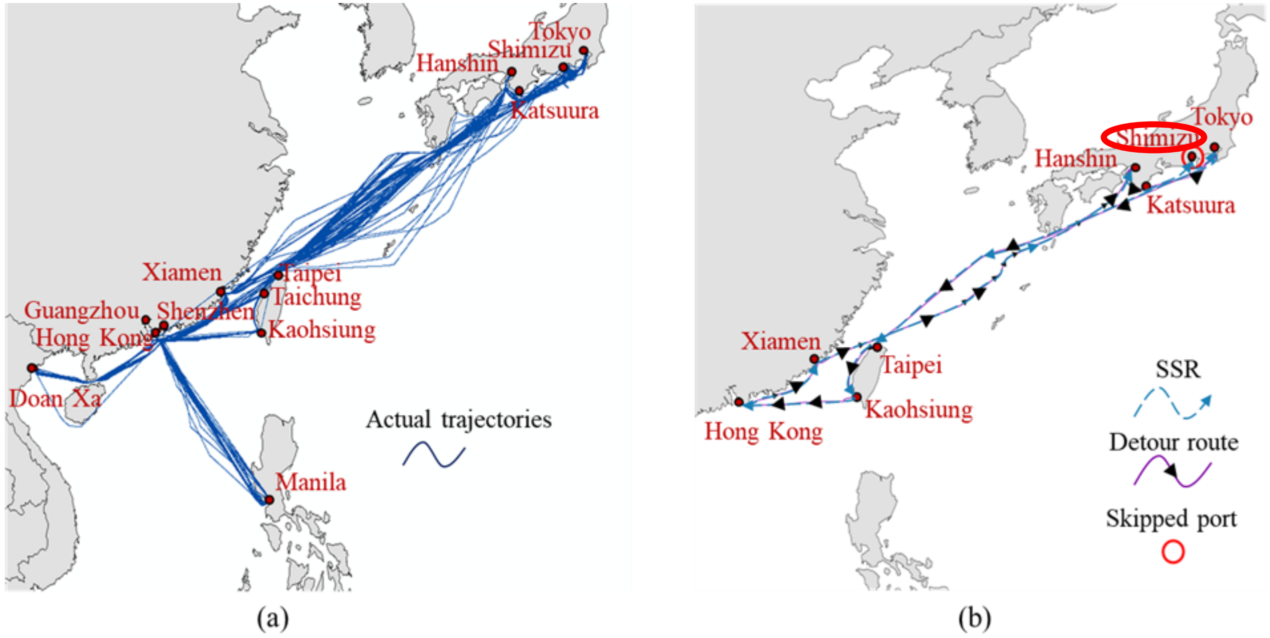


An example of port-skipping in an ordinary case.

- The subset data covers the trajectories of the container vessel with IMO No. 9223758 during 2016, 2019, and 2020
- Based on the detected port calls from **Algorithm 1**, **Algorithm 2** can generate 75 types of trajectory loops and select the loop with the highest frequency as the SSR (i.e., [Kaohsiung (1) → Taichung (2) → Keelung (3) → Ningbo (4) → Dalian (5) → Tianjin (6) → Qingdao (7) → Lianyungang (8)])
- In May 2020, a detour loop is identified by the data-driven framework as [Kaohsiung (1) → Keelung (3) → Ningbo (4) → Dalian (5) → Tianjin (6) → Qingdao (7) → Lianyungang (8)]

Applications Schedule recovery scenario analysis

Case 2: Port-skipping on a route with external-port insertion



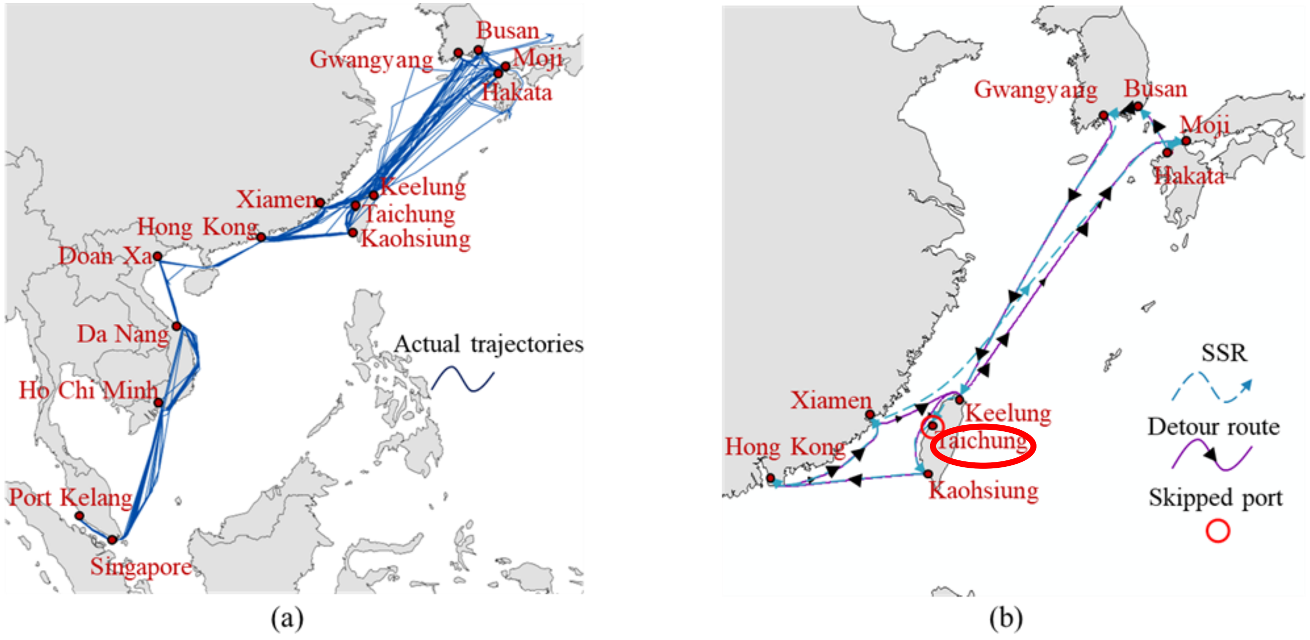
An example of port-skipping on a route with external-port insertion.

- Fig (a) illustrates the shipping trajectories of the vessel with IMO NO. 9233648 from January 2016 to December 2020.
- Based on the shipping trajectories of the China-Japan segments, the determined SSR is [Hong Kong (1) → Xiamen (2) → Hanshin (3) → Shimizu (4) → Tokyo (5) → Taipei (6) → Kaohsiung (7)]
- In May 2018, a detour loop is identified as [Hong Kong (1) → Xiamen (2) → Hanshin (3) → Katsuura (external) → Tokyo (5) → Taipei (6) → Kaohsiung (7)]

Applications

Schedule recovery scenario analysis

Case 3: Port-skipping on a route with internal-port insertion

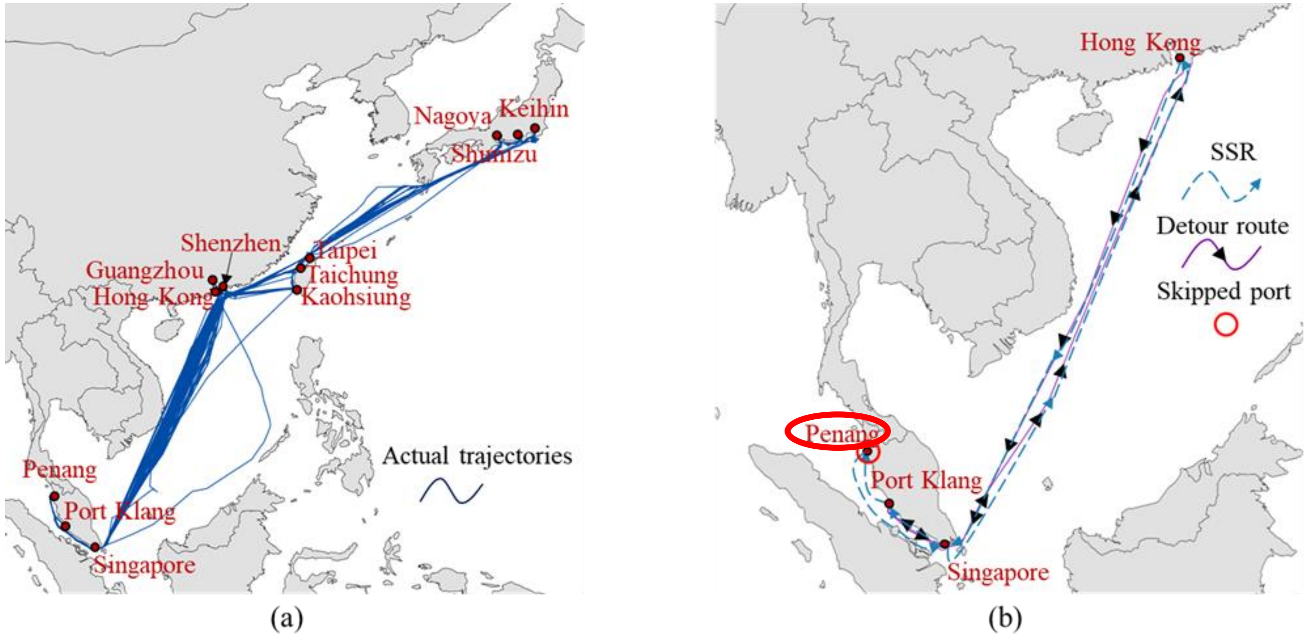


An example of port-skipping on a route with internal-port insertion

- The shipping trajectories of the vessel with IMO No. 9319090 from January 2017 to December 2020 are depicted in Fig (a).
- The SSR is determined as [Gwangyang (1) → Keelung (2) → Taichung (3) → Kaohsiung (4) → Hong Kong (5) → Xiamen (6) → Moji (7) → Hakata (8) → Busan (9)].
- In May 2020, a detour loop is identified as [Gwangyang (1) → Keelung (2) → Kaohsiung (4) → Hong Kong (5) → Xiamen (6) → Keelung (2) → Moji (7) → Hakata (8) → Busan (9)]

Applications Schedule recovery scenario analysis

Case 4: Port-skipping on a route with a backhaul voyage

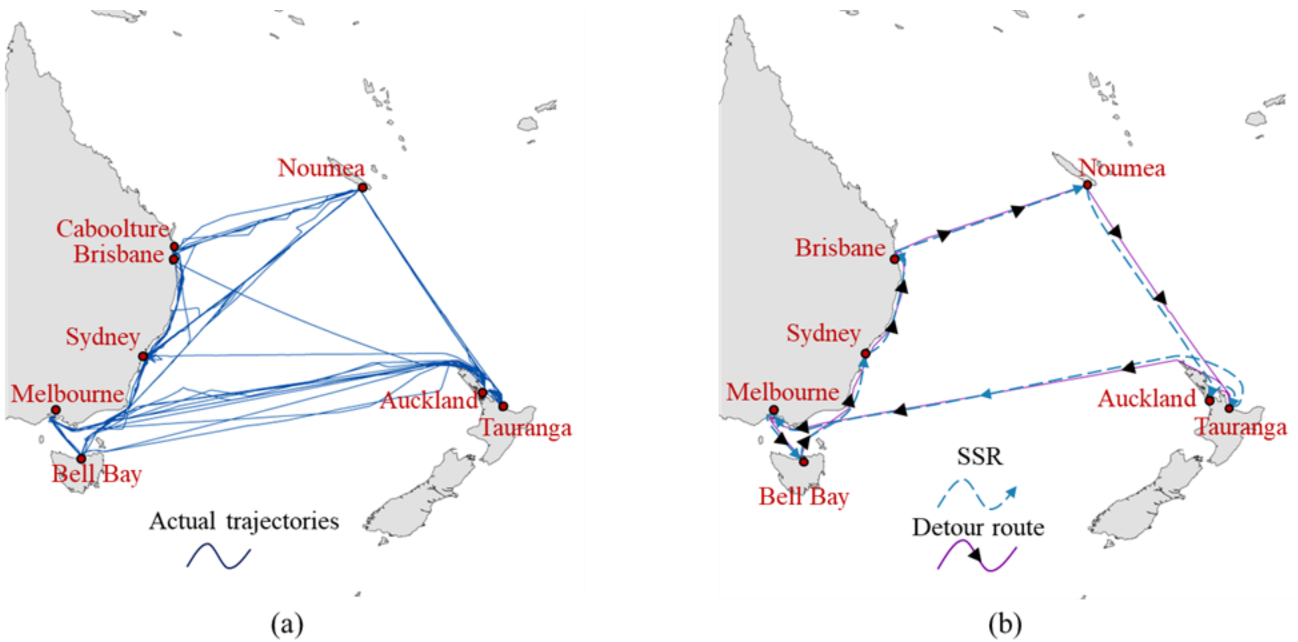


An example of port-skipping on a route with backhaul shipping

- The vessel with IMO No. 9302695 was mostly operated on the routes between China and the Malay Peninsula from January 2016 to December 2020.
- The SSR is determined as [Hong Kong (1) → Singapore (2) → Port Klang (3) → Penang (4) → Singapore (2)]
- After standardization, the standardized SSR is denoted as ([Hong Kong (1) → Singapore (2) → Port Klang (3) → Penang (4)] and the remaining one is saved to the backhaul segment ([Singapore (2)])
- In November 2018, a detour loop is denoted as [Hong Kong (1) → Singapore (2) → Port Klang (3) → Singapore (2)]

Applications Schedule recovery scenario analysis

Case 5: A detour route crossing over the routine loop



An example of a detour route crossing over the routine loop

If a detour route is derived from a trajectory loop with a different origin port from the SSR, a detour route may cross over the routine loop.

- During 2016 and 2020, the vessel with IMO No. 9347982 was always engaged in liner shipping on the fixed segments between Australia and New Zealand.
- The SSR determined by **Algorithm 2** is [Noumea (1) → Auckland (2) → Tauranga (3) → Melbourne (4) → Bell Bay (5) → Sydney (6) → Brisbane (7)].
- In March 2016, a detour loop is denoted as [Auckland (2) → Tauranga (3) → Melbourne (4) → Bell Bay (5) → Sydney (6) → Brisbane (7) → Noumea (1) → Tauranga (3) → Auckland (2)].
- Only swapping, no port-skipping.

Conclusion

Based on a series of tailored data mining algorithms, a novel data-driven framework is developed, which can make use of AIS data to stepwise screen port calls, extract standard service routes, detect anomalous vessel tracks, and finally achieve port-skipping identification.

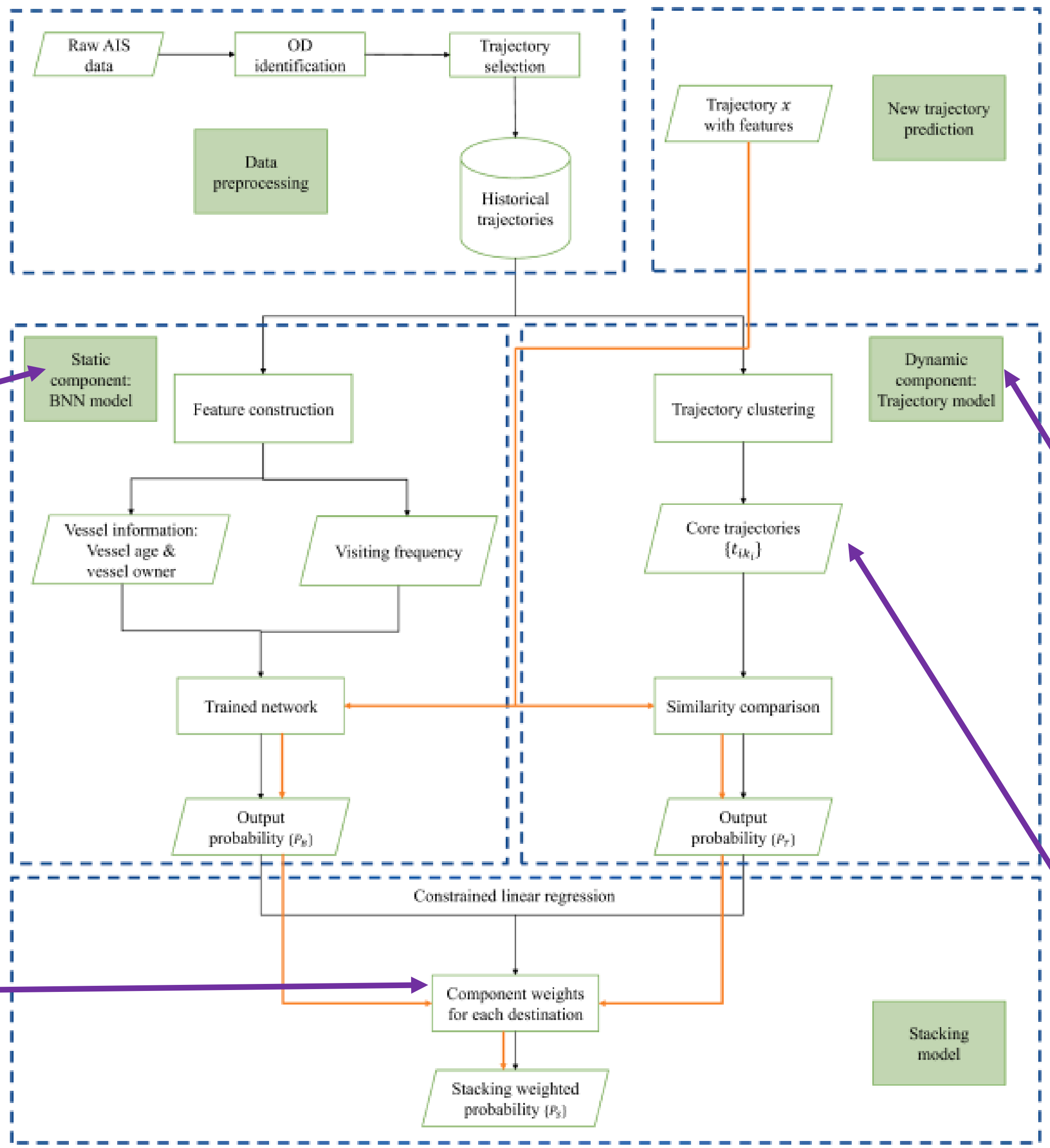
The visualized overall identification results suggest a positive correlation between traffic flow and the frequency of port-skipping at most ports. However, Singapore, due to its exceptional location and unique role in the global shipping network, exhibits the anomaly of high traffic flow and low frequency of port-skipping.

6 Vessel destination prediction

IDEAS Innovation-driven Education and Scholarship | Faculty of Business 工商管理學院 | Department of Logistics & Maritime Studies 物流及航運學系

Methodology

A static model to predict the destination of a vessel either just before or just after it starts its voyage



A stacking model for vessel destination prediction based on a Bayesian neural network (BNN) and a dynamic model

A dynamic model to update its prediction for the vessel's destination synchronously

A modified DBSCAN clustering method for trajectory clustering and core trajectory identification

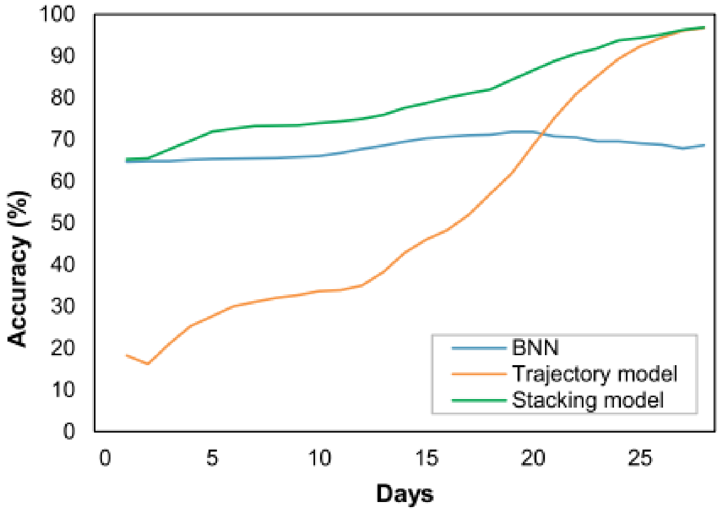
A multi-response constrained linear regression model to obtain the optimal weights for the static and dynamic

Results

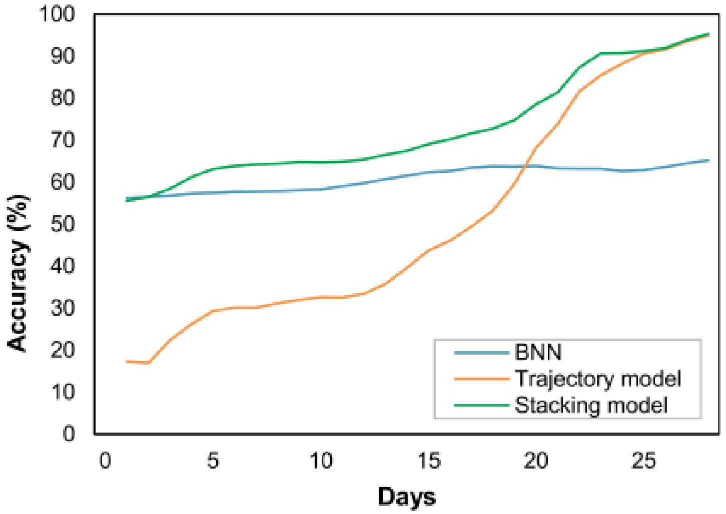
Core trajectories of China

Core trajectories of Japan

Core trajectories of Korea



Prediction accuracy on the training set



Prediction accuracy on the testing set

Thank you for your attentions!