

# Real-Time Management of Vessel Carbon Dioxide Emissions Based on Automatic Identification System Database Using Deep Learning

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# Abstract

- ▶ In this study, we propose an effective method using deep learning to strengthen real-time vessel carbon dioxide emission management. We propose a method to predict real-time carbon dioxide emissions of the vessel in three steps: (1) convert the trajectory data of the fixed time interval into a spatial-temporal sequence, (2) apply a long short-term memory (LSTM) model to predict the future trajectory and vessel status data of the vessel, and (3) predict the carbon dioxide emissions.
- ▶ Automatic identification system (AIS) data of a liquefied natural gas (LNG) vessel were selected as the sample and we reconstructed the trajectory data with a fixed time interval using cubic spline interpolation. Applying the interpolated AIS data, the carbon dioxide emissions of the vessel were calculated based on the International Towing Tank Conference (ITTC) recommended procedures.

# Abstract

- ▶ The experimental results are twofold. First, it reveals that vessel emissions are currently under-estimated. This study clearly indicates that the actual carbon dioxide emissions are higher than those reported. The finding offers insight into how to accurately measure the emissions of vessels, and hence, better execute a greenhouse gases (GHGs) reduction strategy.
- ▶ Second, the LSTM model has a better trajectory prediction performance than the recurrent neural network (RNN) model. The errors of the trajectory endpoint and carbon dioxide emissions were small, which shows that the LSTM model is suitable for spatial-temporal data prediction with excellent performance.
- ▶ Therefore, this study offers insights to strengthen the real-time management and control of vessel greenhouse gas emissions and handle those in a more efficient way.

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# 1. Introduction

The slide features a white background with a decorative graphic on the right side. This graphic consists of several overlapping, semi-transparent green triangles and polygons in various shades of green, ranging from light lime to dark forest green. The shapes are arranged in a way that they appear to be layered, creating a sense of depth and movement. The overall aesthetic is clean and modern.

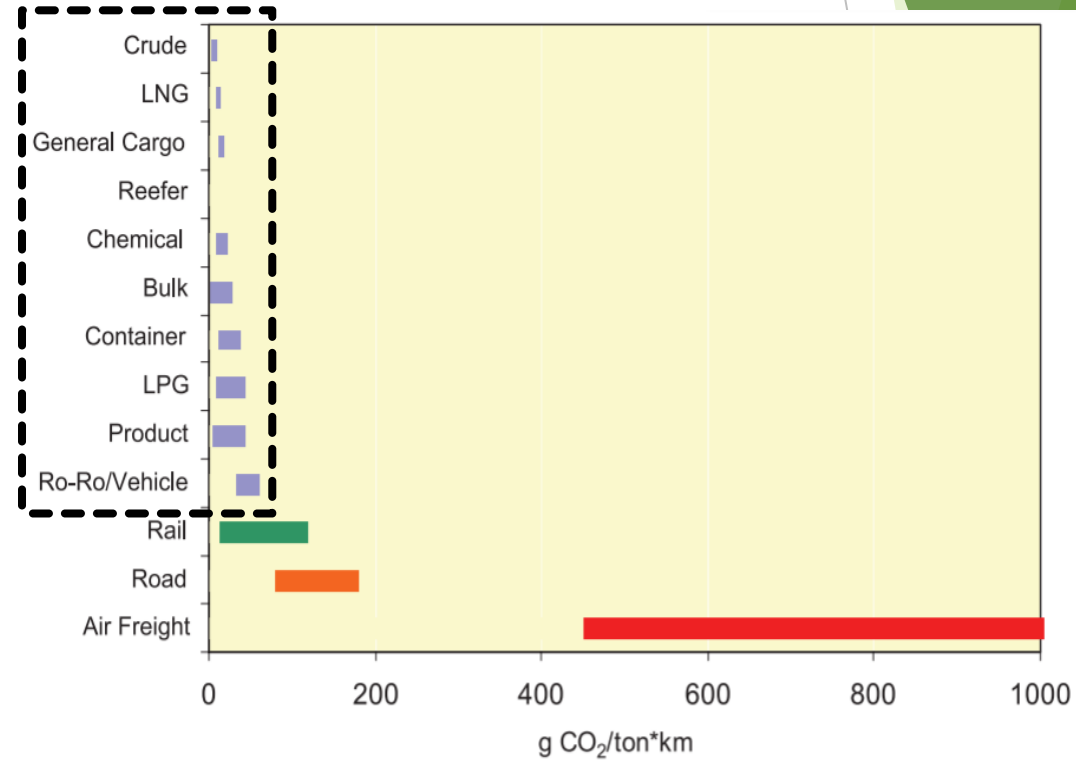
# Greenhouse gas emissions from shipping

## ► Characteristics of Shipping

- Shipping is the least green house gas and air pollutant emitting mode of transportation in ton\*kilo base compared to rail, road and air freight.
- About 90 % of internal trade depend on shipping.

## ► Fourth Greenhouse Gas Study 2020 by IMO

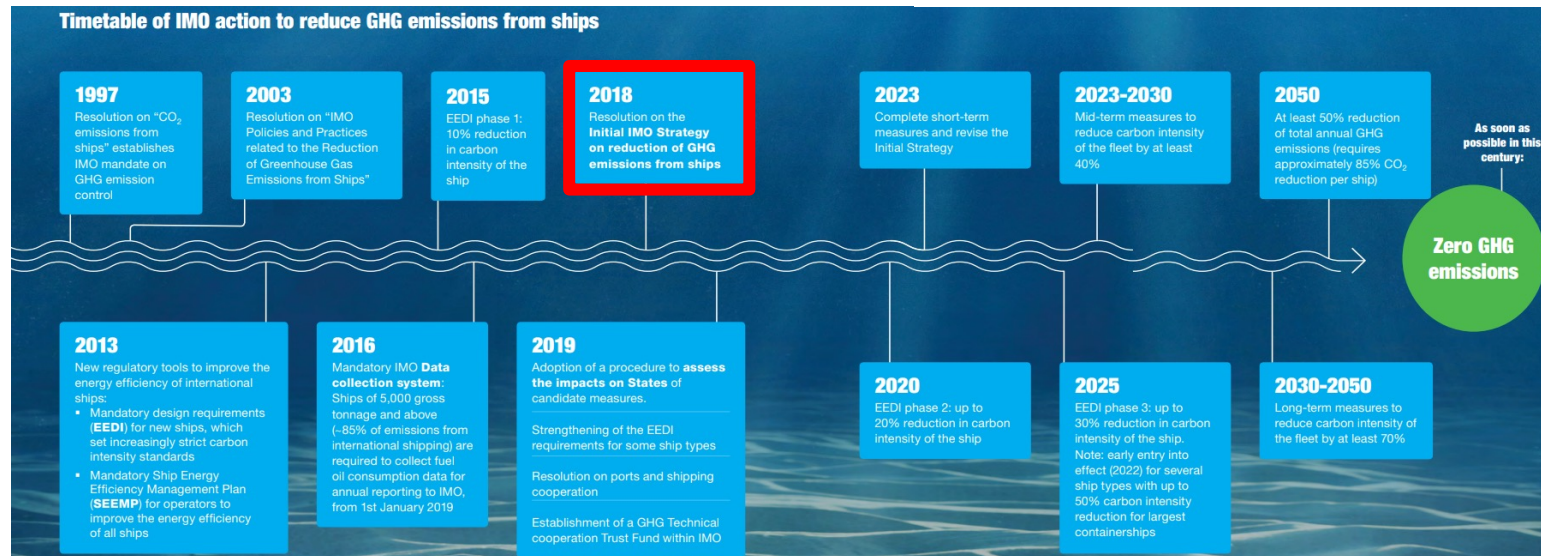
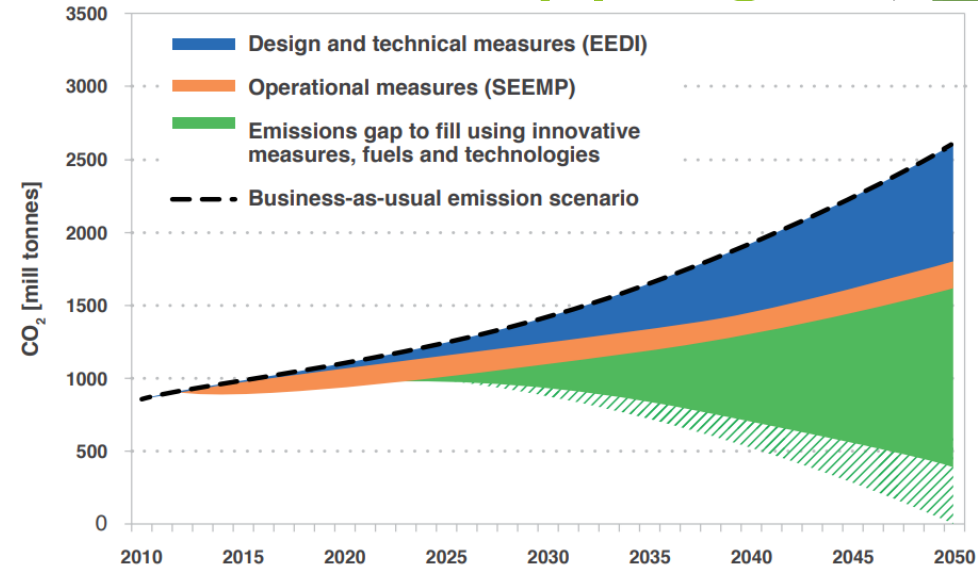
- The share of shipping emissions in global anthropogenic emissions has increased from 2.76% in 2012 to 2.89% in 2018.
- The greenhouse gas emissions of shipping increased from 977 million tonnes (Mt) in 2012 to 1,076 Mt in 2018, a 9.6% rise. Over this period the carbon intensity of shipping operations improved by about 11%, but these efficiency gains were outstripped by growth in activity.
- By 2050 emissions are projected to have increased by up to 50% relative to 2018, despite further efficiency gains, as there is expected to be continued growth of transport demand.



Typical range of CO2 efficiencies

# Greenhouse gas emissions from shipping

- ▶ The initial IMO GHG strategy in 2018
  - ▶ In 2050, at least 50% reduction of total annual GHG emissions (requires approximately 85% CO<sub>2</sub> reduction per ship)



# Sustainable Maritime Development in Japan

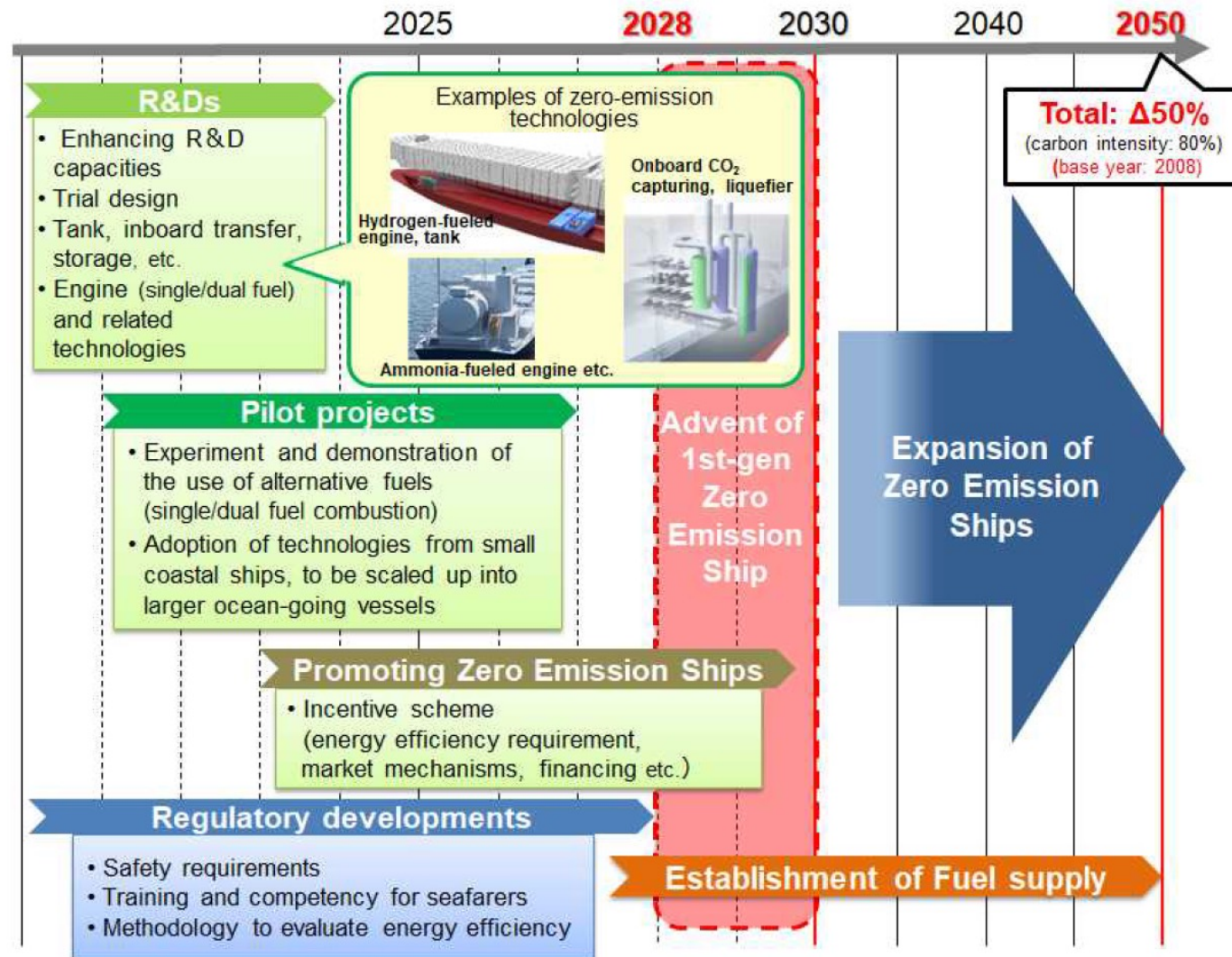
► By Koji Sekimizu (Former Secretary General, IMO) in 2011

1	Global Standards (GS)	for shipping at IMO covering safety, environmental protection, security and facilitation
2	Energy Efficiency (EE)	covering technical and operational measures for efficient fuel consumption based on the basic recognition that fossil energy resources are not infinite and every effort must be made to save energy resources
3	New Technology (NT)	for safety, environmental protection, security, clean energy and efficient operation of shipping to meet the present and future challenges
4	Education and Training (ET)	to ensure a continuous supply of quality seafarers and maritime experts required for all aspects of maritime industries including shipbuilding and maritime equipment manufacturing industries
5	Maritime Security (MS)	covering application of international measures for maritime security, anti-piracy measures, law enforcement mechanisms for maritime zone security and the supply chain security
6	Maritime Traffic Management (MTM)	in straits and sea areas of significant importance covering cooperative mechanisms of littoral States, public-private partnership for future systems and realization of the Marine Electronic Highways.
7	Maritime Infrastructure (MI)	including aids to Navigation, Search and Rescue, port facilities and technical cooperation to ensure availability of proper maritime infrastructure in all parts of the world.



# Roadmap to Zero Emission from International Shipping in Japan

- ▶ National R&D Strategy for Zero Emission Ship in 2020
- ▶ The Japan Ship Technology Research Association (JSTRA) and the Ministry of Land, Infrastructure, Transport and Tourism (MLIT)



# 1.1 Greenhouse gases (GHG) of vessel

Major international mechanisms to combat climate change, reduce air pollution in the global shipping sector, and regulate ship emissions,

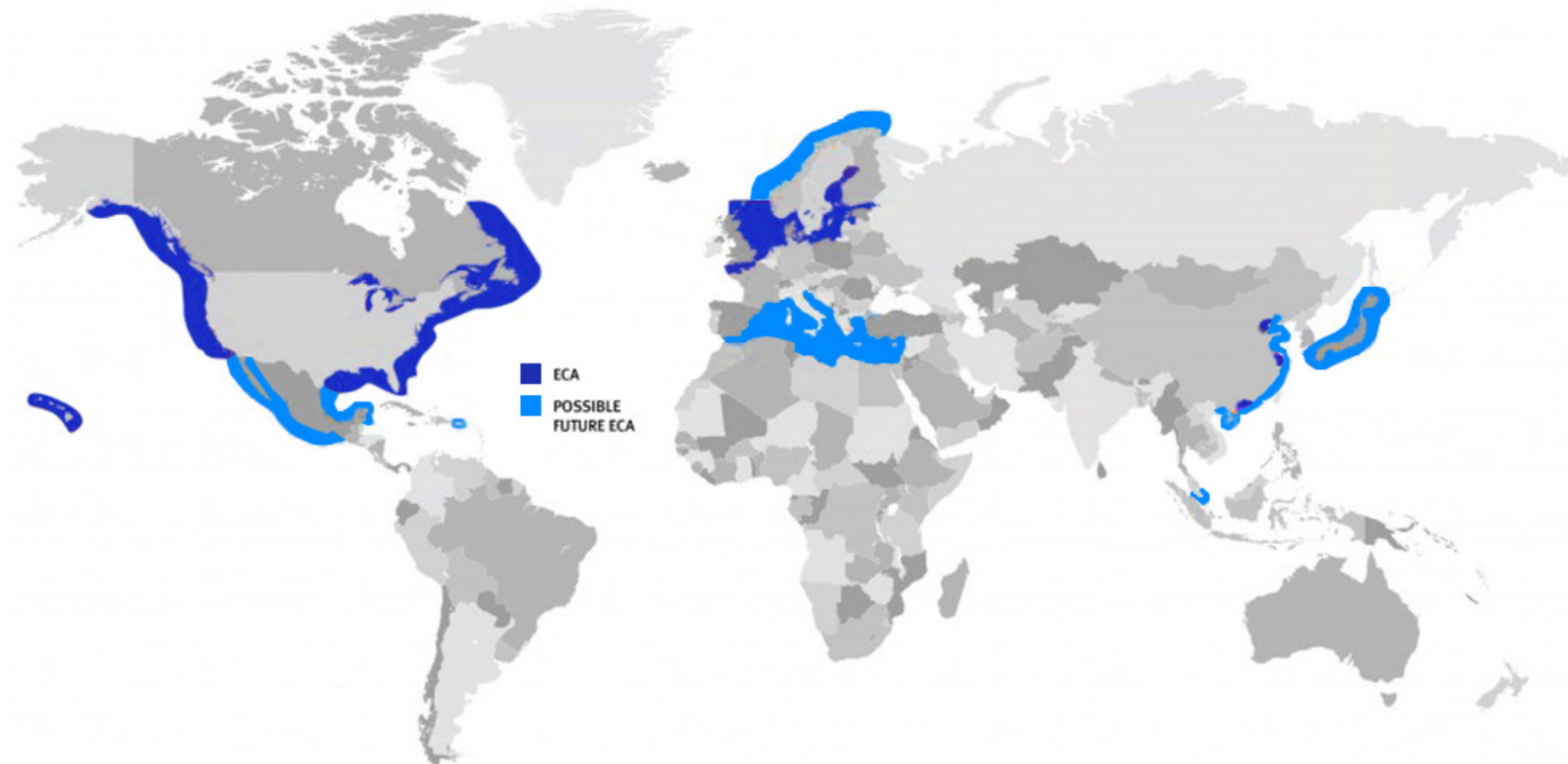
- UNFCCC: United Nations Framework Convention on Climate Change
- UNCLOS: United Nations Convention on the Law of the Sea
- IMO: International Maritime Organization

IMO: regulate international maritime transportation. Its main responsibility is to create a regulatory framework for the shipping industry, set safety standards, and prevent marine pollution from ships.

- ECAs(Emission control controlled): Areas to minimize pollution in designated marine areas.
- The special emission control is divided into two aspects, which set the emission limits of sulfur oxides and nitrogen oxides
  - SECAs(Sulfur emission control areas)
  - NECAs(Nitrogen emission control areas)

# 1.1 Greenhouse gases (GHG) of vessel - Sulphur Restriction Order

ECAs



## 1.1 Greenhouse gases (GHG) of vessel – EEDI, SEEMP

The International Maritime Organization introduced two energy efficiency measures aimed at solving greenhouse gas emissions from the shipping sector:

Energy Efficiency Design Index (EEDI) ;

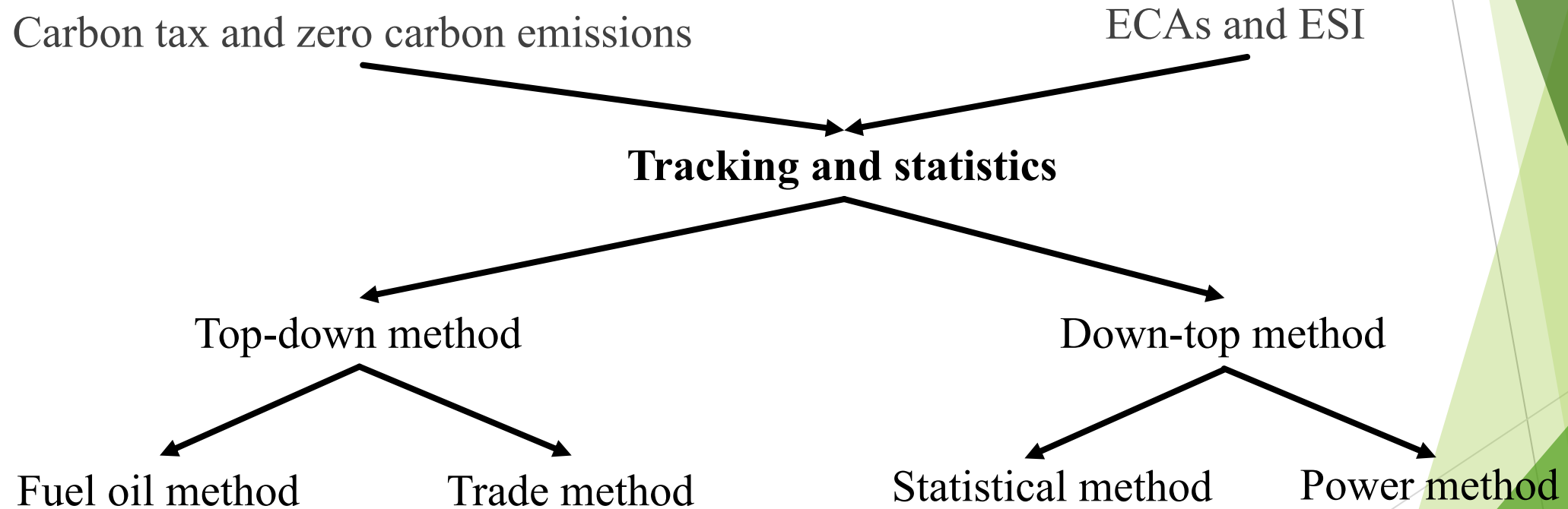
Ship Energy Efficiency Management Plan (SEEMP).

# 1.1 Greenhouse gases (GHG) of vessel – ESI

World Port Climate Initiative (WPCI). The World Port Climate Initiative released the "Environmental Ship Index" (ESI) in 2010, which aims to significantly reduce the emissions of nitrogen, sulfur oxides, and carbon dioxide in the longer term, and encourages ports to provide shipping companies that use ESI certified ocean-going ships entry fee discount, or reduce its tonnage fee.



# 1.1 Greenhouse gases (GHG) of vessel - Tracking



# 1.1 Greenhouse gases (GHG) of vessel - Tracking

**Fuel oil method:** the total emissions are obtained based on the fuel oil statistics multiplied by the estimated average emission factor, and then the total emissions are allocated according to the ship type;

**Trade method:** the trade law refers to the method of calculating emissions based on the parameters of ocean freight turnover, cargo type, etc., combined with certain experience.

# 1.1 Greenhouse gases (GHG) of vessel - Tracking

**Statistical method:** the statistical method refers to the static statistics of the data, such as the number of ships entering and leaving the port, and the combination of ship classification, engine power distribution, activity mode classification and emission factor estimation, and finally the ship engine power and activity time to estimate emissions Methods;

**Power method:** the core of the power method is to obtain high-resolution ship power information through real-time monitoring of the ship's operating conditions, determine engine load and operating conditions, and use different operating conditions for ship engines emission factors to establish an emission inventory. (AIS)



# 1.1 Greenhouse gases (GHG) of vessel - AIS



VTS Center

(Source: SAAB BRAZIL)

1. The increasing number of ships and types of ships have increased the workload of duty personnel. AIS data is more reliable than VTS radar signals, and is more and more widely used in maritime traffic management, improving management efficiency.

# 1.1 Greenhouse gases (GHG) of vessel - AIS

**AIS (Automatic Identification System):** the system was originally developed as a **collision avoidance tool** to enable commercial vessels to ‘see’ each other more clearly in all conditions and improve the helmsman’s information about his surrounding environment. AIS does this by continuously transmitting a vessels identity, position, speed and course along with other relevant information to all other AIS equipped vessels within range. Combined with a shore station, this system also offers port authorities and maritime safety bodies the ability to manage maritime traffic and reduce the hazards of marine navigation.

# 1.1 Greenhouse gases (GHG) of vessel - AIS

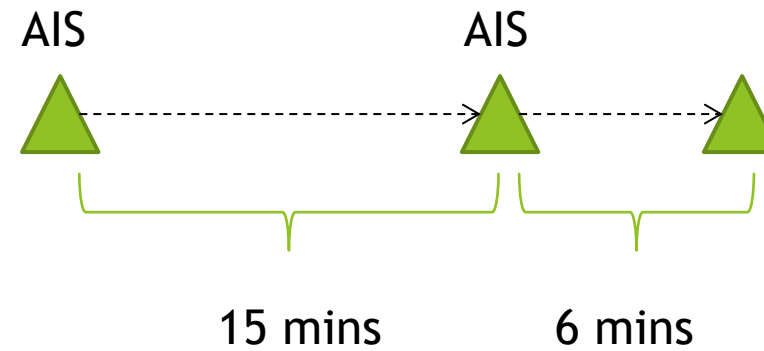
For example:  
Vessel trajectory record will disappear for 15 minutes or 6 minutes



- a. Artificial shutdown
- b. Equipment problem



Small calculation result of ship emissions in this region



# 1.1 Greenhouse gases (GHG) of vessel - AIS

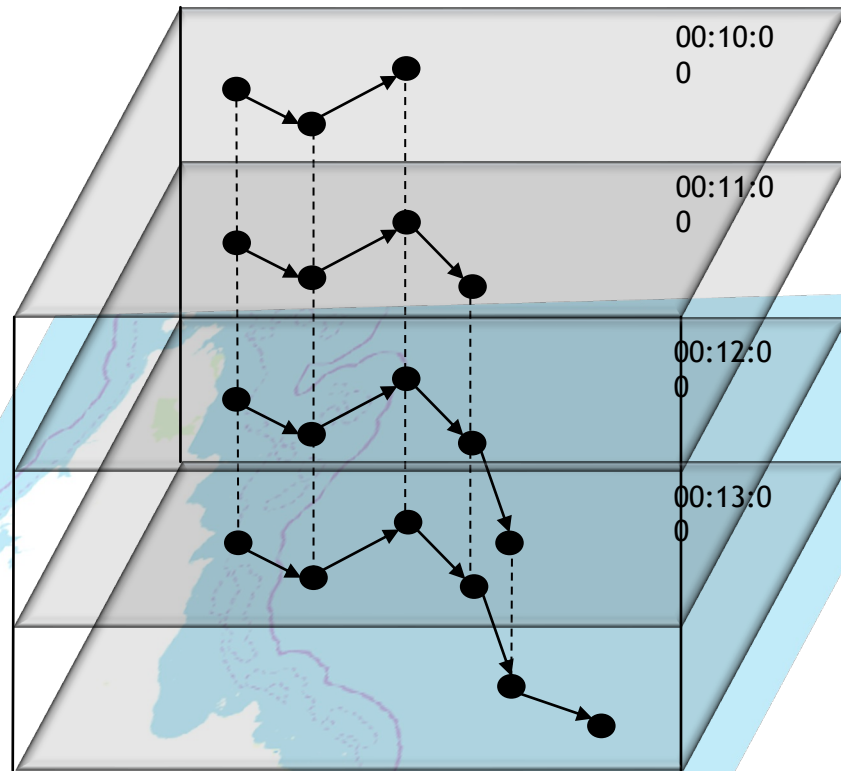
dt_pos_utc	mmsi	longitude	latitude	sog	cog
1/1/2016 0:32	310028000	117.9136	-18.3856	10.7	211
1/1/2016 0:33	310028000	117.9117	-18.3883	11	211
1/1/2016 0:34	310028000	117.9104	-18.3908	10.7	210.7
1/1/2016 1:17	310028000	117.8405	-18.5008	10.5	210.9
1/1/2016 1:18	310028000	117.8392	-18.5029	10.4	211.3
1/1/2016 1:19	310028000	117.8379	-18.505	10.5	211.9
1/1/2016 1:20	310028000	117.8363	-18.5076	10.6	210.8
1/1/2016 1:21	310028000	117.8345	-18.5106	10.5	211.6
1/1/2016 1:21	310028000	117.8343	-18.511	10.5	211.6
1/1/2016 1:22	310028000	117.8332	-18.5127	10.6	210.9
1/1/2016 1:22	310028000	117.8329	-18.5131	10.6	210.7
1/1/2016 1:23	310028000	117.8324	-18.5139	10.6	211
1/1/2016 1:23	310028000	117.8321	-18.5144	10.6	211.6
1/1/2016 1:23	310028000	117.8311	-18.5161	10.6	210.9
1/1/2016 1:25	310028000	117.8285	-18.5203	10.6	208

Missing



SMALL

## 1.2 Vessel trajectory prediction in deep learning



Generally, vessel trajectory data can be represented as a set of multi-dimensional spatial-temporal sequences  $\{(p_1, a_1, t_1), (p_2, a_2, t_2), (p_3, a_3, t_3), \dots, (p_n, a_n, t_n)\}$ , where  $p_i$  is the position (longitude, latitude),  $a_i$  is the data attribute (SOG, COG), and  $t_i$  is the recording time of the AIS data.

## 1.2 Vessel trajectory prediction in deep learning

Some scholars applied DL to predict the future **destination of ships**, predict the **time of arrival of ships**, predict **the probability of collision**, predict the **flow of ships** in a certain sea area in the future, and so on.

However, few scholars are currently concerned about using AIS data to predict the emissions of ships in the future.

## 1.2 Vessel trajectory prediction in deep learning

When we can obtain the ship's future exhaust emissions and emission location, we can inform the ship in advance of the time and location of the exhaust emission limit zone, so that the ship is ready to slow down and change to use low-sulfur oil.

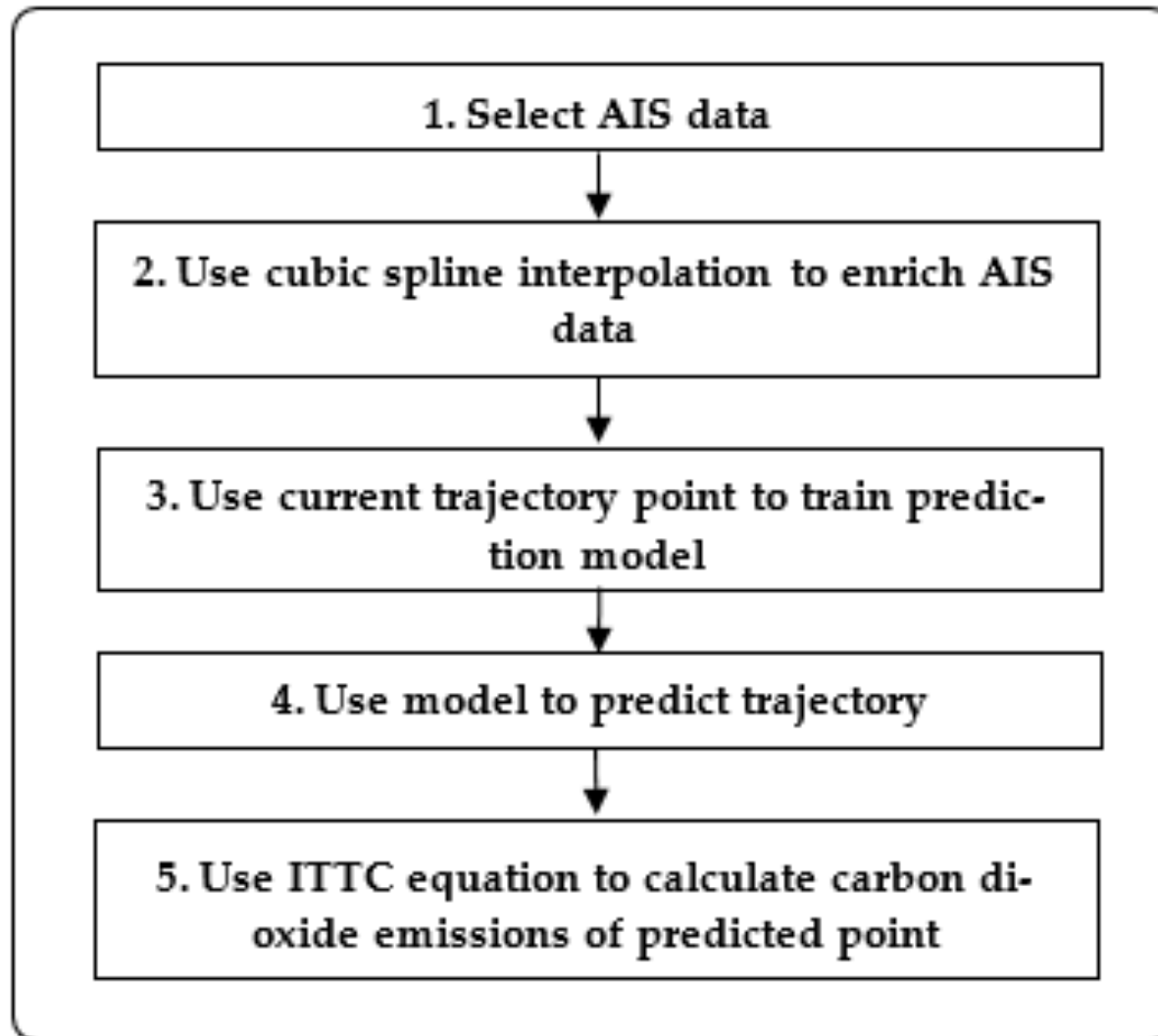


## 1.3 The aim of study

The purpose of this study is to strengthen the monitoring and early warning of CO<sub>2</sub> emissions from ships through AIS data and deep learning. The pre-processed AIS data provides detailed movement status and geographic location of the ship, and **enhances the estimation accuracy** of carbon dioxide emissions. Under the framework of deep learning, the **prediction of the ship's carbon dioxide emissions** and positions can provide early warning services for ships, tell them when and where to enter emission-restricted areas, and help ships prepare for speed reduction and replacement of fuel oil in advance. After the emission restriction zone, the prediction technology can also provide ships with the carbon dioxide emissions required to enter the port, help ships decide to use a **reasonable speed**, and **save carbon emissions costs**.



## 1.3 The aim of study

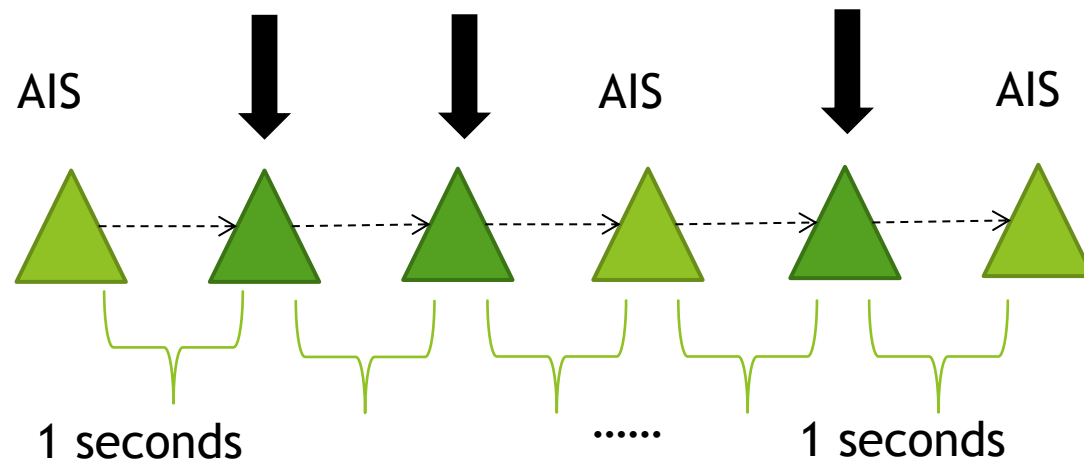


## 2. Model description

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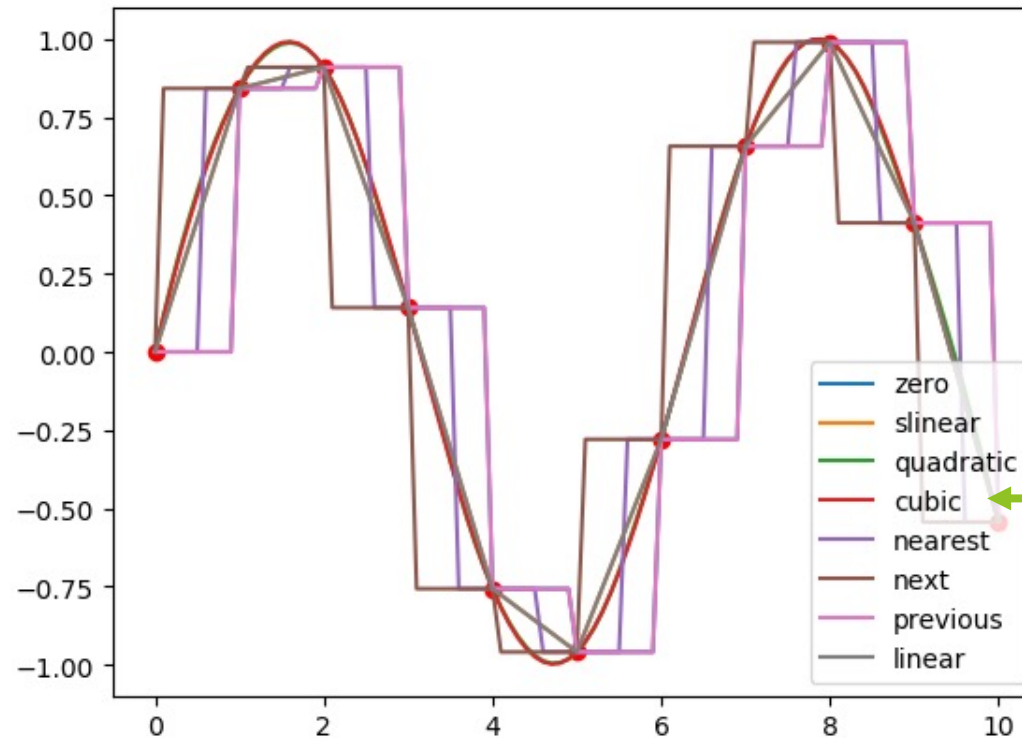
## 2.1 Cubic spline interpolation model

In the previous section, we discussed the problem of missing AIS data. We considered using cubic spline interpolation to repair AIS data. Using the restored AIS data to estimate CO2 emissions is more than using the original AIS data



## 2.1 Cubic spline interpolation model

- 1. Cubic spline interpolation method
- Lagrange interpolation
- Newton interpolation
- Hermite interpolation
- Piecewise interpolation
- Spline interpolation  
(Fast, effective and smooth curve)



# 2.1 Cubic spline interpolation model

We suppose that the interval of trajectory data is  $[a,b]$ , divide  $[a,b]$  into  $n$  intervals, like  $[(x_0, x_1), (x_1, x_2), \dots, (x_{n-1}, x_n)]$ ,  $x_0 = a, x_n = b$ , the function expression for each interval is  $S(x)$ . Cubic spline means that the curve of each interval is a cubic equation  $S_i(x)$  and meet interpolation conditions,  $S(x_i) = y_i$ . Meet the condition of smooth curve that  $S_i(x), S_i'(x), S_i''(x)$  are continuous function. Solved equation (Bartels et al. (1998)) is as follows:

$$S_i(x) = a_i + b_i(x - x_i) + c_i(x - x_i)^2 + d_i(x - x_i)^3 \quad (1)$$

$$S_i'(x) = b_i + 2c_i(x - x_i) + 3d_i(x - x_i)^2 \quad (2)$$

$$S_i''(x) = 2c_i + 6d_i(x - x_i) \quad (3)$$

Where  $S_i(x)$ : Cubic spline model expression,  $a_i, b_i, c_i, d_i$ : Parameters to be solved.

According to  $S_i(x)$  must meet interpolation conditions,  $S(x_i) = y_i$ , and equations (1), (2) and (3), we can get the equation as follows:

$$a_i = y_i \quad (4)$$

$$h_i = x_{i+1} - x_i \quad (5)$$

$$a_i + b_i h_i + c_i h_i^2 + d_i h_i^3 = y_{i+1} \quad (6)$$

According to continuous function conditions,

$$S_i'(x_{i+1}) = S_{i+1}'(x_{i+1}) \quad (7)$$

$$S_i''(x_{i+1}) = S_{i+1}''(x_{i+1}) \quad (8)$$

we can get the equation as follows:

$$b_i + 2h_i c_i + 3h_i^2 d_i = b_{i+1} \quad (9)$$

$$2c_i + 6h_i d_i = 2c_{i+1} \quad (10)$$

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Carbon dioxide emissions estimation and prediction based on AIS vessel trajectory data restoration using deep learning

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$$d_i = \frac{m_{i+1} - m_i}{6h_i} \quad (m_i = 2c_i) \quad (11)$$

Use equation (4), (10), (11) to input equation (6), we can get the equation as follows:

$$b_i = \frac{2y_{i+1} - y_i}{h_i} - \frac{2}{h_i} m_i - \frac{h_i}{6} (m_{i+1} - m_i) \quad (12)$$

Use equation (4), (10), (11), (12) to input equation (9), we can get the equation as follows:

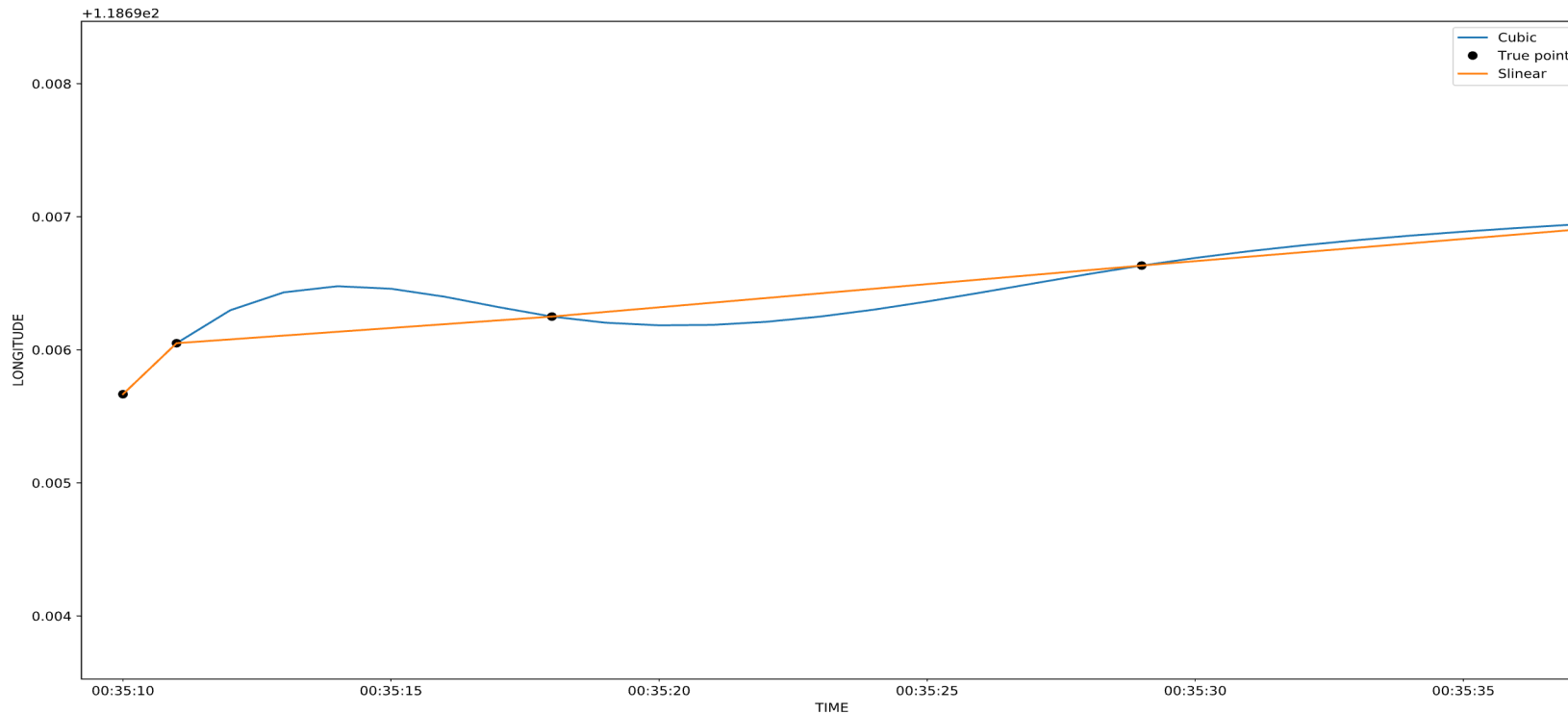
$$h_i m_i + 2(h_i + h_{i+1})m_{i+1} + h_{i+1}m_{i+2} = 6 \left[ \frac{2y_{i+1} - y_i}{h_i} - \frac{2y_i - y_{i-1}}{h_{i-1}} \right] \quad (13)$$

We build linear equations with  $m$  as the unknown ( $m_0 = 0, m_n = 0$ ):

$$\begin{bmatrix} 1 & 0 & 0 & 0 & \dots & 0 \\ h_0 & 2(h_0 + h_1) & h_1 & 0 & \dots & 0 \\ 0 & h_1 & 2(h_1 + h_2) & h_2 & \dots & 0 \\ 0 & 0 & h_2 & 2(h_2 + h_3) & h_3 & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & h_{n-2} & 2(h_{n-2} + h_{n-1}) & h_{n-1} \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} m_0 \\ m_1 \\ m_2 \\ m_3 \\ \vdots \\ m_{n-1} \\ m_n \end{bmatrix} = \begin{bmatrix} 0 \\ \frac{2y_1 - y_0}{h_1} - \frac{2y_0 - y_{-1}}{h_{-1}} \\ \frac{2y_2 - y_1}{h_2} - \frac{2y_1 - y_0}{h_1} \\ \vdots \\ \frac{2y_{n-1} - y_{n-2}}{h_{n-1}} - \frac{2y_{n-2} - y_{n-3}}{h_{n-2}} \\ 0 \end{bmatrix} \quad (14)$$

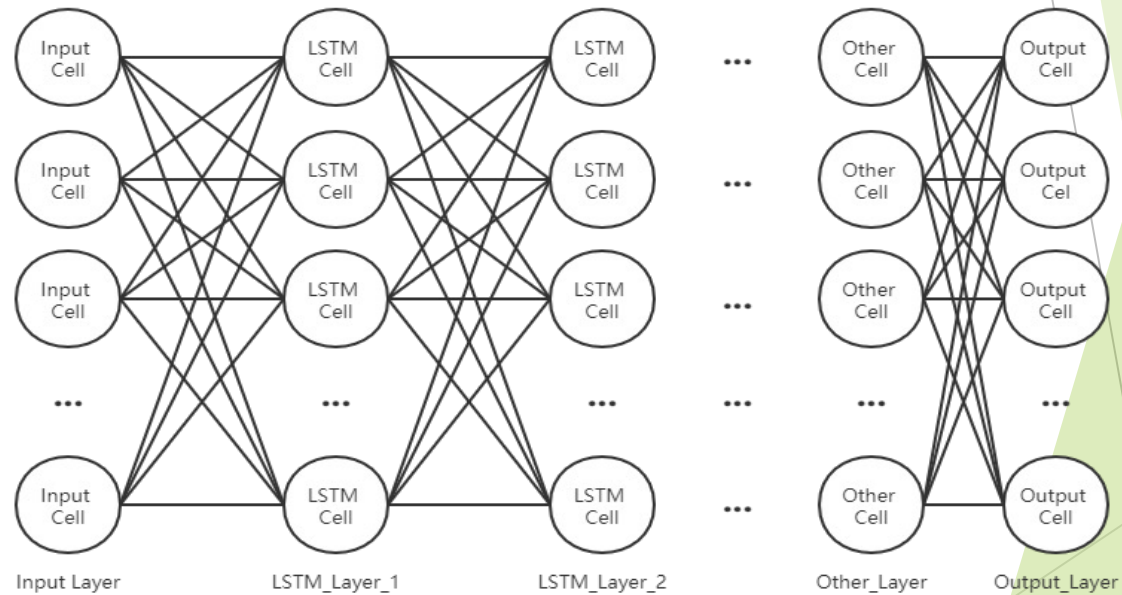
## 2.1 Cubic spline interpolation model - result

We could find that the line connecting the original data points was no longer a simple straight orange line, but had become a blue curve, which was more in line with the actual situation.



## 2.2 Long short-term memory model

The LSTM model (Hochreiter et.al. (1997)) is a variant of RNN. The RNN cannot learn longer histories data, resulting in a gradient decline or even disappearance at further time steps. To solve this problem, LSTM model introduces storage units and unit states to control information transfer based on RNN.



## 2.2 Long short-term memory model

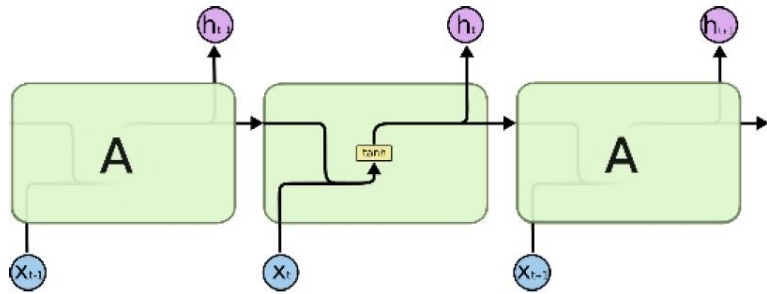
There are four gates:

Forget Gate,

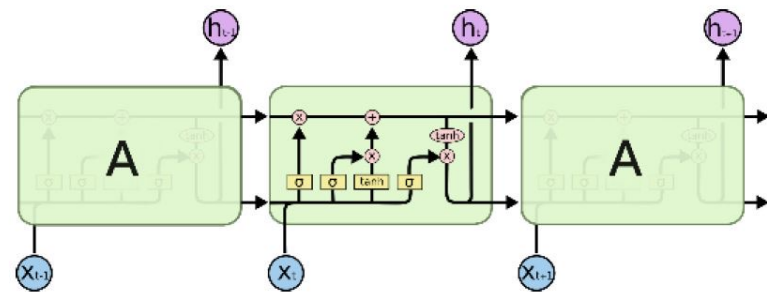
Input Gate,

Update Gate,

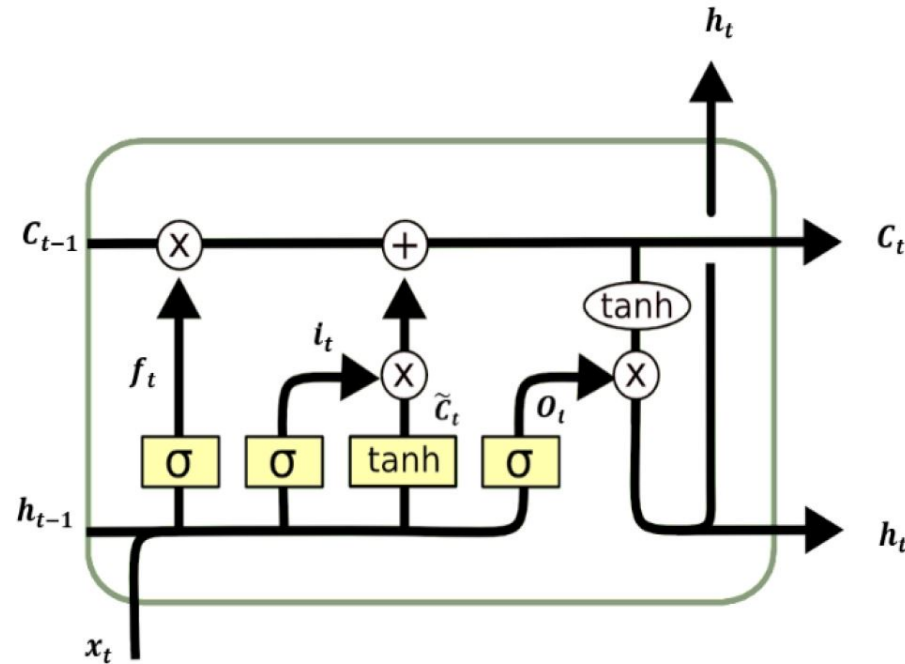
Output Gate



(a) Structure of the RNN



(b) Structure of LSTM



(c) Detailed structure of LSTM



## 2.3 $CO_2$ emission estimation model

In this study, we adopted the ITTC recommended procedure (2017) to estimate vessel resistance. It is necessary to derive total resistance first. Total resistance can be denoted as (Molland, A. F. et al. (2016)):

$$R_T = \frac{1}{2} C_T \rho S V^2$$

Where  $R_T$ : total resistance,  $C_T$ : total resistance coefficient,  $\rho$ : density of water,  $S$ : wetted surface of the hull,  $V$ : SOG.

## 2.3 $CO_2$ emission estimation model

$C_T$ , total resistance coefficient, can denoted as:

$$C_T = C_F + C_A + C_{AA} + C_R$$

Where  $C_F$ : frictional resistance coefficient,  $C_A$ : incremental resistance coefficient,  $C_{AA}$ : air resistance coefficient,  $C_R$ : Residual resistance coefficient.

## 2.3 CO<sub>2</sub> emission estimation model

Based on calculated total resistance of vessel, estimating required power when the vessel sailing at speed  $V$  in calm sea condition can be calculated by considering the components of propulsion efficiencies. Installed power is the power required to tow vessel with speed  $V$  in a calm sea. Service power can be derived from (Molland, A. F. et al. (2016)):

$$P_I = \frac{R_T V}{(\eta_o \eta_R)} + m$$

Where  $P_I$ : Installed power,  $\eta_T$ : Transmission efficiency,  $\eta_D$ : Quasi-Propulsive Coefficient, and  $m$ : Sea margin.

## 2.3 CO<sub>2</sub> emission estimation model

Fuel oil consumption is calculated by using Specific Fuel Oil Consumption (SFOC) on table 1 released in third IMO study. As the vessel engine gets older, an efficiency of the engine goes down and advent of technology make a newer engine more efficient.

<b>Engine age</b>	<b>SSD (IMO)</b>	<b>MSD (IMO)</b>	<b>HSD (IMO)</b>
<b>before 1983</b>	205	215	225
<b>1984-2000</b>	185	195	205
<b>post 2001</b>	175	185	195

## 2.3 $CO_2$ emission estimation model

Marine LNG  $CO_2$  emissions factor is 2.75. So  $CO_2$  emission estimation model can denote as:

$$E_i = \sum P_i \times SFOC \times 2.75 \times T$$

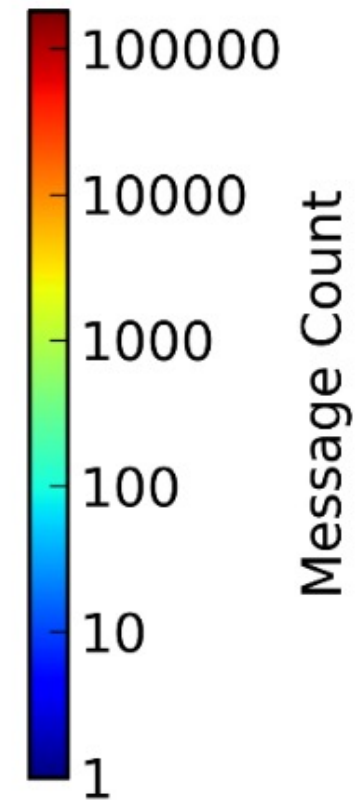
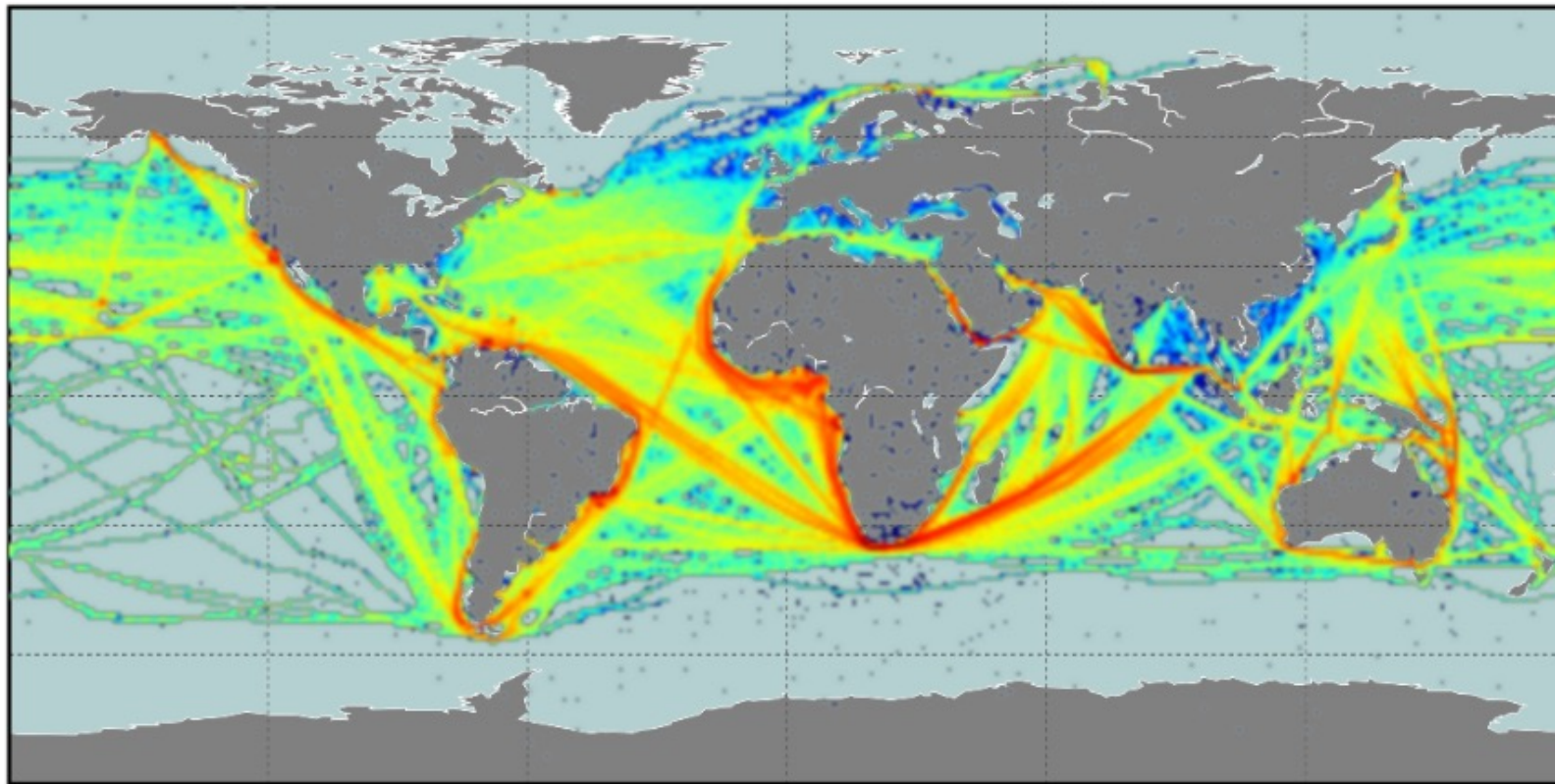
Where  $E_i$ : total  $CO_2$  emission, it is calculated by summing the carbon dioxide emissions at each trajectory point,  $T$ : time interval of each track point.

### 3. Experiments and results



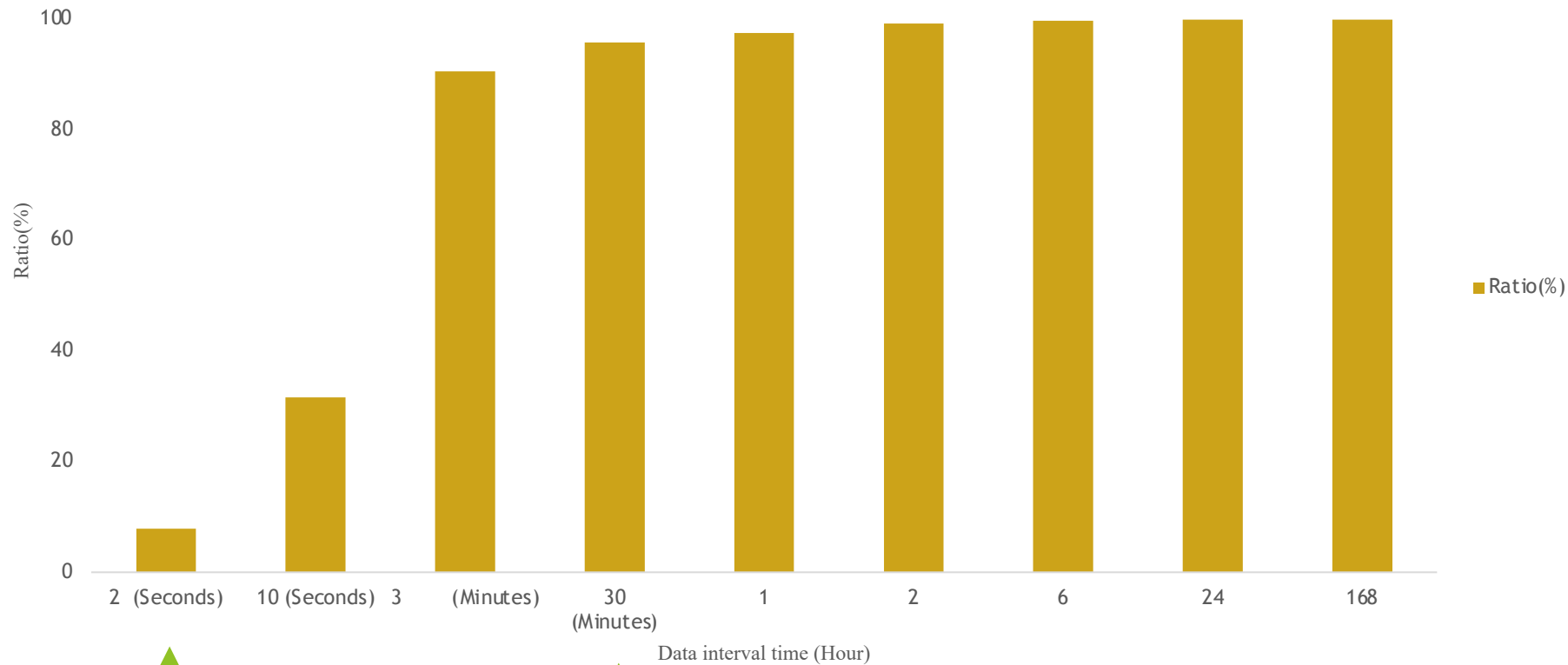
## 3.1 AIS data set analysis

This study used AIS data provided by exactEarth.



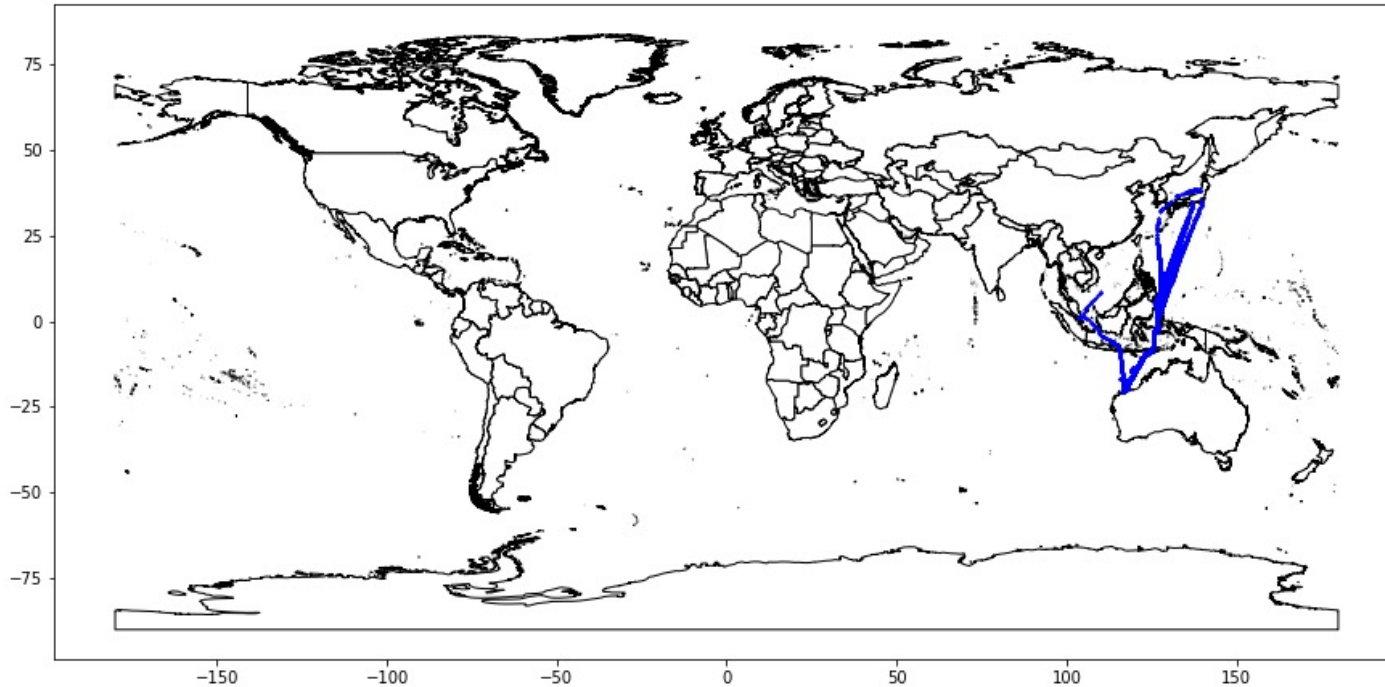
# 3.1 AIS data set analysis

we founded that more than 90% of the data had a time interval of more than 30 minutes. Only about 8% of the data had a time interval of 2 seconds. It should be noted that the total amount of raw data was 51,705,694. Looking at this ratio on a single vessel, the accuracy of the estimated vessel carbon dioxide emissions was not enough. It may be because AIS data collected through satellite shows longer data collecting interval when the vessel was sailing areas with high traffic compare to areas with less traffic.





## 3.1 AIS data set analysis - sample



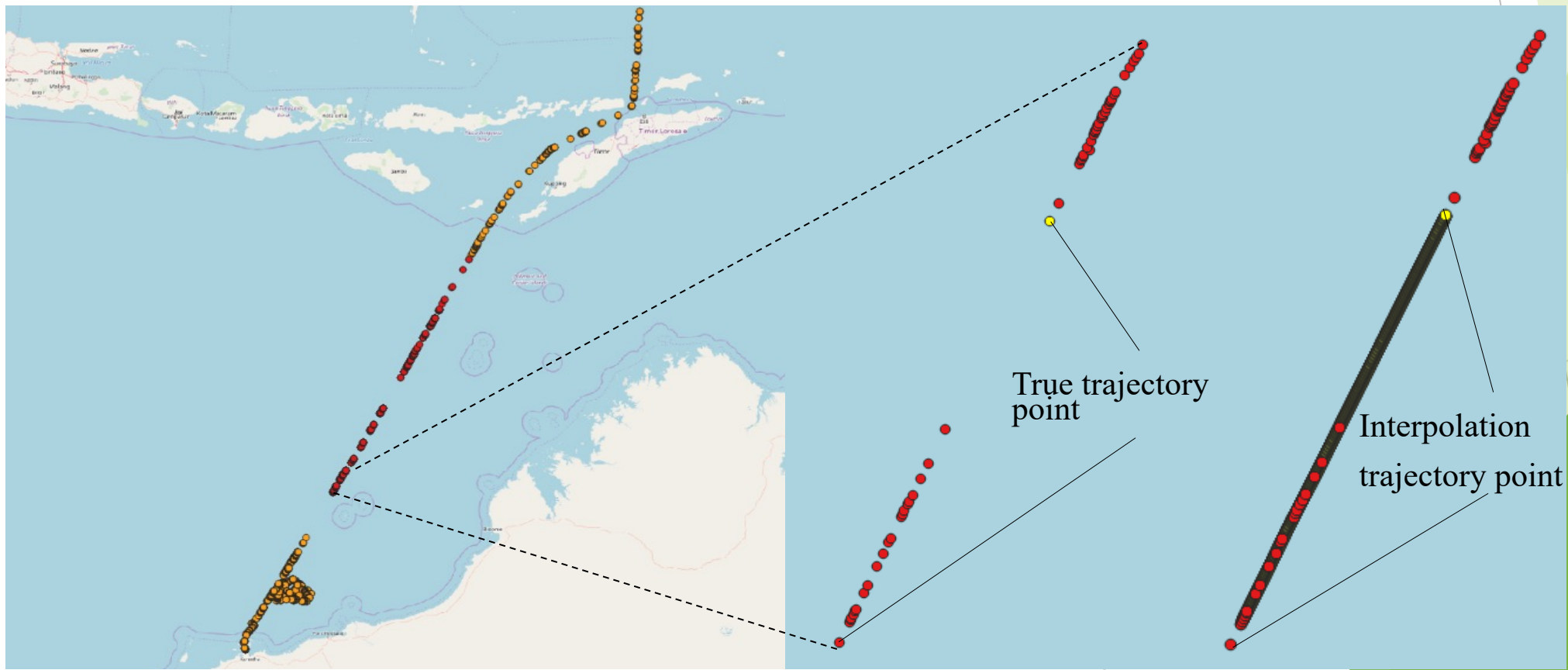
we extracted the vessel track data of MMSI 310028000 from the trajectory database as a sample to illustrate the feasibility of the model. The vessel trajectory over 6 months was shown in Figure. The vessel travels mainly between Japan and Australia, IMO number is “8913174”, built in 1992.

## 3.1 AIS data set analysis - sample

<b>MMSI</b>	<b>TIME</b>	<b>LONGITU DE</b>	<b>LATITUD E</b>	<b>SOG</b>	<b>COG</b>
<b>310028000</b>	00:35:10	118.6957	-17.0403	15.9	24.7
<b>310028000</b>	00:35:11	118.6961	-17.0395	15.8	25.1
<b>310028000</b>	00:35:18	118.6963	-17.0391	15.9	25.1
<b>310028000</b>	00:35:29	118.6966	-17.0383	15.8	25
<b>310028000</b>	00:35:41	118.697	-17.0375	15.8	24.8
<b>310028000</b>	00:35:48	118.6972	-17.0371	15.8	25.2
.....	.....	.....	.....	.....	.....

## 3.2 Cubic spline interpolation model - result

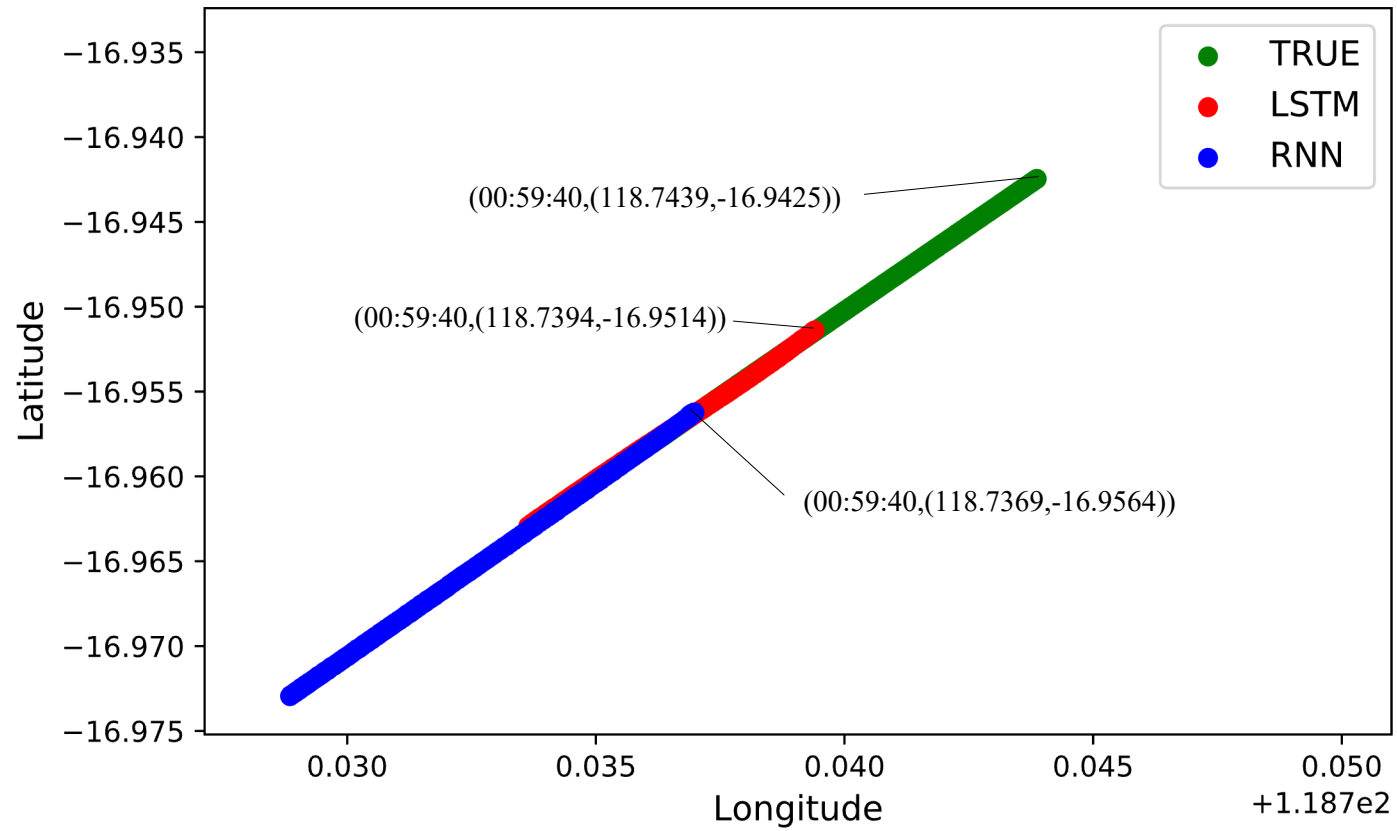
In the actual geographic location, we could see the restoration trajectory after interpolation calculation from Figure, where the yellow point was the trajectory point of the vessel at 00:59:40, the red point was the trajectory point on January 5, orange point was point on other days in January, green point was interpolation points. The amount of data after interpolation calculation changed from 23 to 1,472.



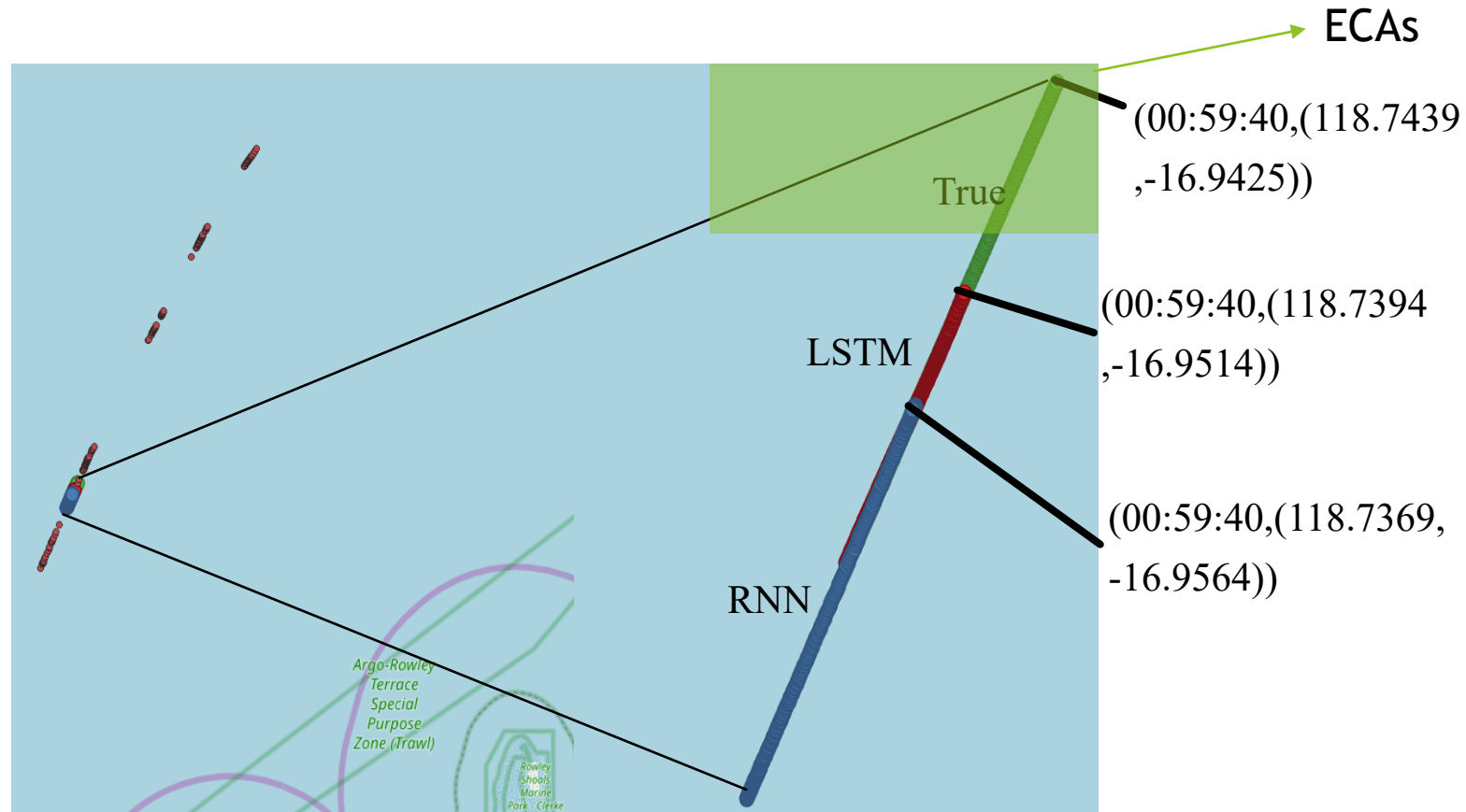
## 3.3 Vessel Trajectory Prediction

<b>Base learning rate</b>	<b>0.001</b>	<b>LSTM_layer_1</b>	<b>256</b>
<b>Optimizer</b>	Adaptive Moment Estimation	LSTM_layer_2	128
<b>Epoch</b>	125	Dropout_layer_1	128
<b>Batch size</b>	138	Dense_layer_1	128
<b>Loss function</b>	Mean Square Error	Dropout_layer_2	128
<b>Activation_1</b>	Tanh	Dense_layer_2	4
<b>Activation_2</b>	Linear	Kernel_initializer	Orthogonal
<b>Train set</b>	938	Validation set	235
<b>Test set</b>	293		

# 3.3 Vessel Trajectory Prediction

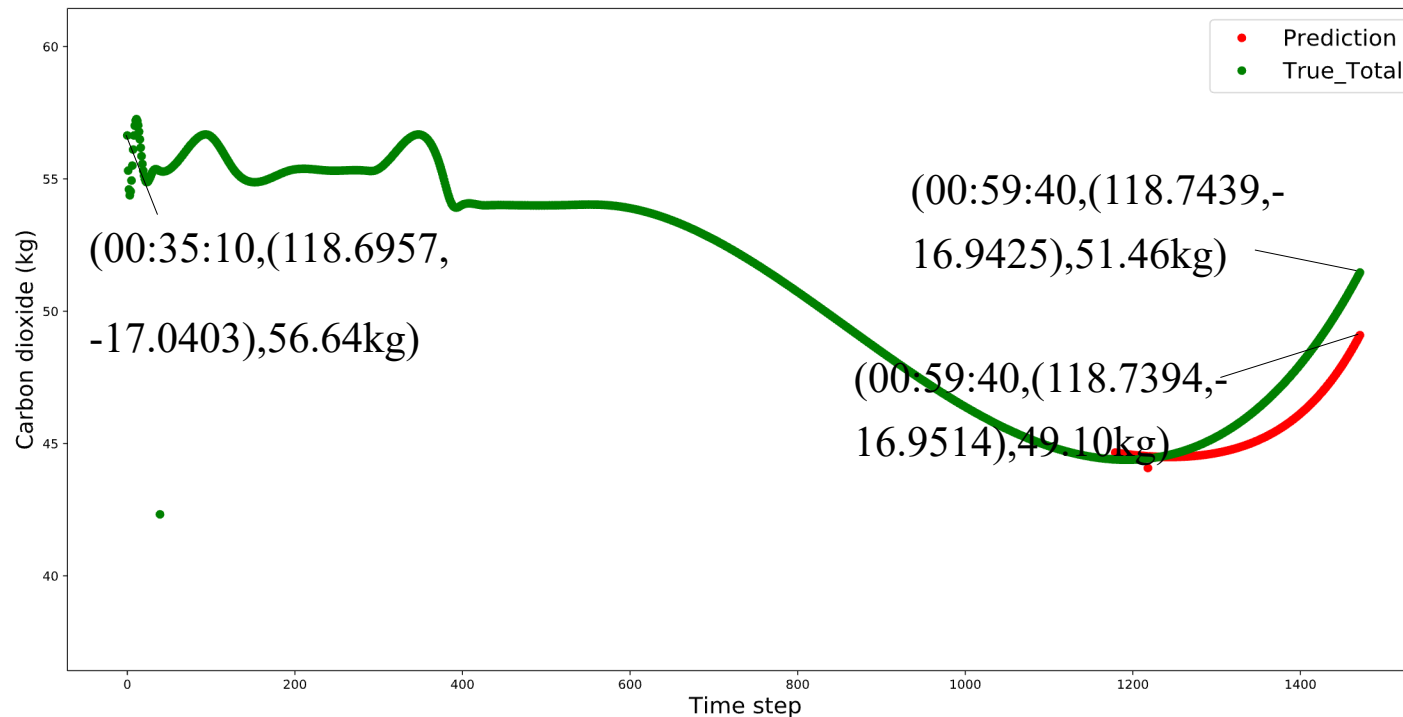


# 3.3 Vessel Trajectory Prediction

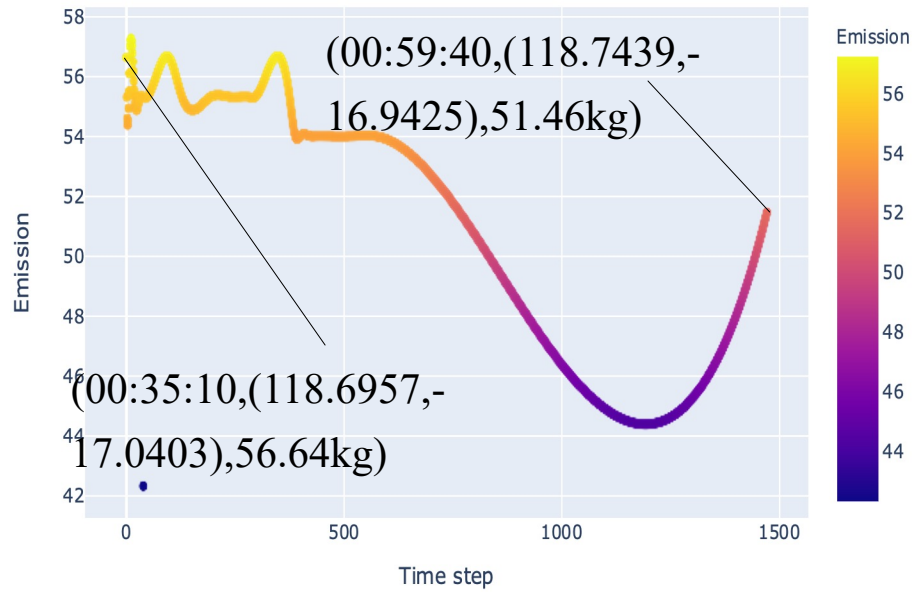


## 3.4. Carbon Dioxide Estimation

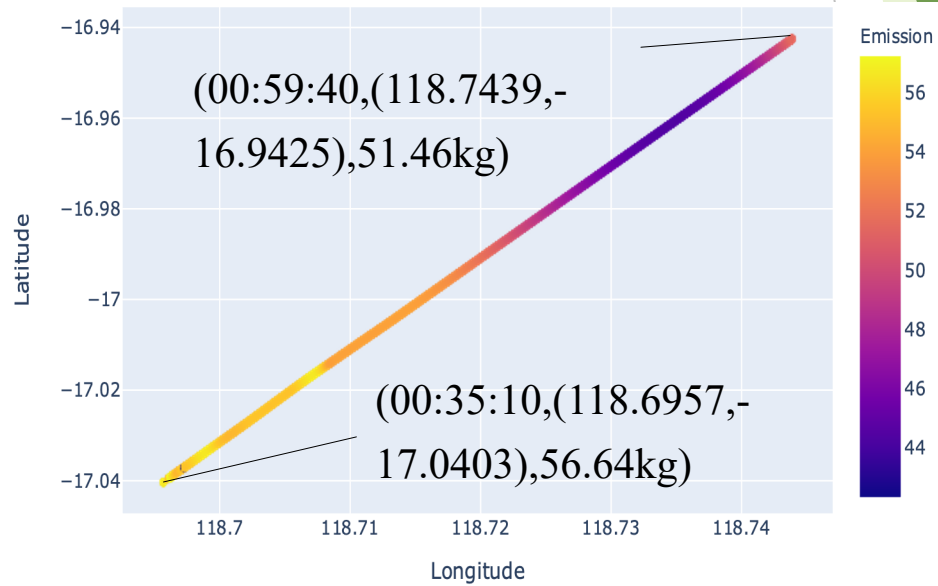
We could get the emissions of the vessel at 00:35:10-00:59:40 was 47,169 kg, but we calculated the vessel carbon dioxide emissions after interpolation was 74,926 kg. This was 27,757 kg more carbon dioxide emissions than traditional estimation methods.



# 3.4. Carbon Dioxide Estimation



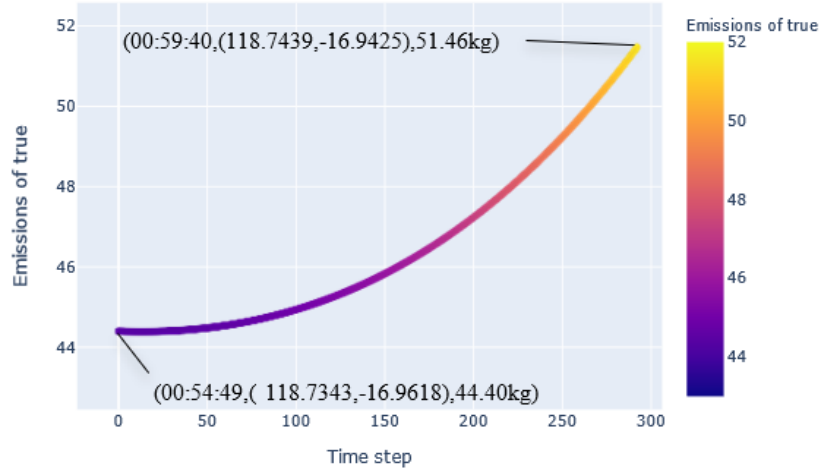
(a)



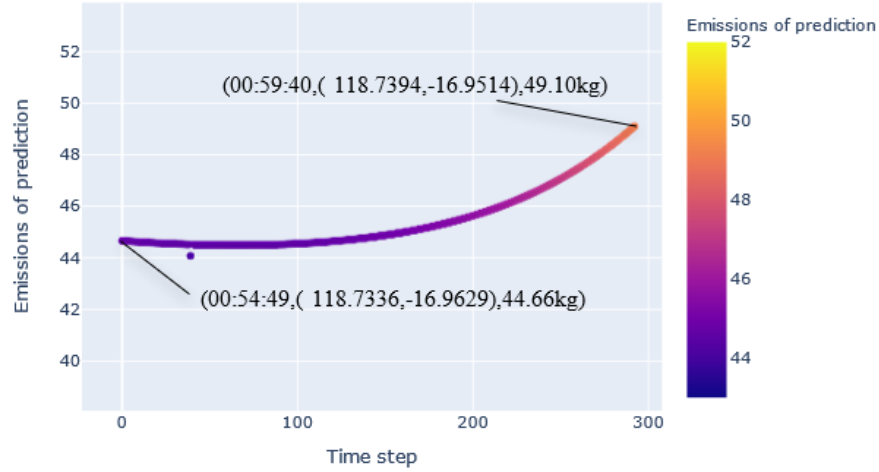
(b)



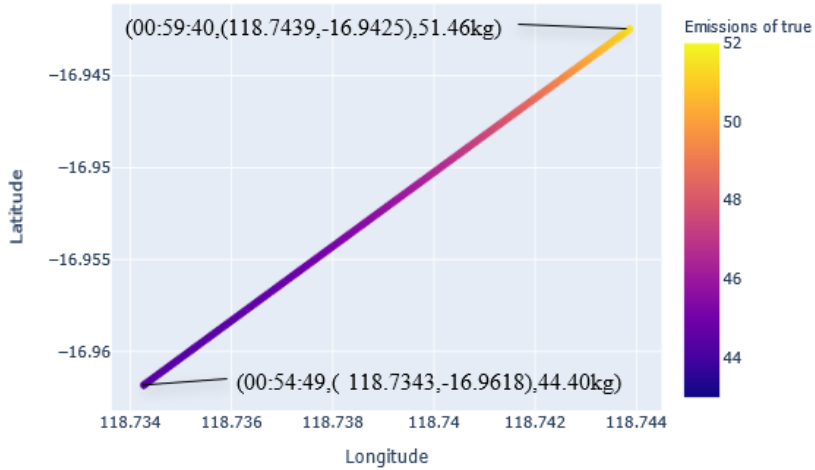
# 3.4. Carbon Dioxide Estimation



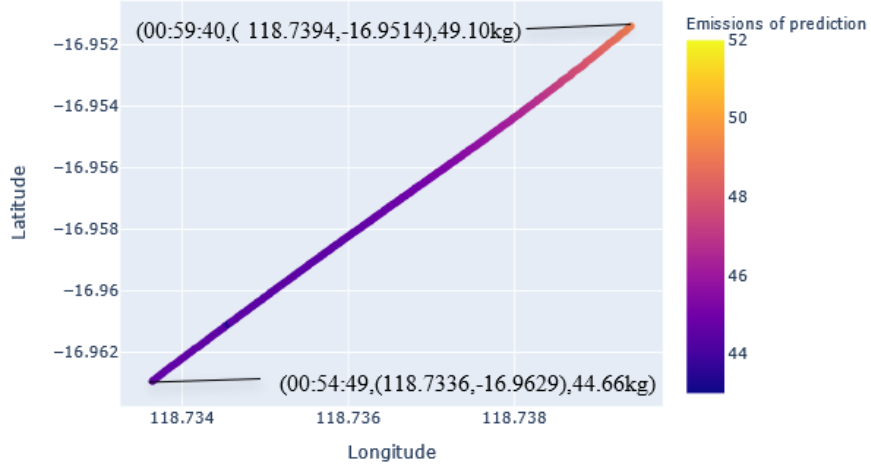
(a)



(b)



(c)



(d)

# Conclusion

- 1) Based on the investigation of the basic characteristics of maritime traffic, **ITTC** is used to estimate the ship's greenhouse gas emissions to **monitor and track the ship's GHG emissions behavior**.
- 2) It is also recommended to use the **LSTM model** to predict the future location and carbon dioxide emissions of the ship. In order to **enhance the safety of ships** in narrow seas and **strengthen the supervision** of ships greenhouse gas emissions.

Thank you for your kind attention.



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