Toros University FEASS Journal of Social Sciences
Special Issue on 2nd International Symposium of Sustainable Logistics "Circular Economy"
Toros Üniversitesi İİSBF Sosyal Bilimler Dergisi 2. Uluslararası Sürdürülebilir Lojistik "Dögüsel Ekonomi" Sempozyumu Özel Sayı

ISSN: 2147-8414

ARAŞTIRMA MAKALESİ/ **RESEARCH ARTICLE**

Greenhouse Gas Emission And Their Trend Prediction Using AIS and Trade Data

AIS ve Ticaret Verileri Kullanılarak Sera Gazı Emisyonu ve Eğilim Tahmini

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ABSTRACT

Due to decarbonization and greenhouse gas (GHG) emission reduction attempts nowadays, liquefied natural gas (LNG) has become widely used as an alternative marine fuel. As Japan is the top global LNG importer and one of the largest crude oil importers, this study focuses on LNG and tanker shipping and their emissions in Japan, and import volumes. In this study, the emission estimation model is constructed based on the Holtrop-Mennen power prediction method. Using automatic identification system (AIS) data, fuel consumption and GHG emissions are estimated. Next, long term GHG emission is predicted using the Japan trade statistics. Combining the vessel movement data and trade statistics, GHG emission in Japan is projected to decline over years for tankers, and to remain stable for LNG carriers. The results could be considered in formulating environmental and trade policy. It is hoped the study will provide useful insights for zero emission projects and implementations in Japan.

Keywords: Automatic identification system, ship emission, greenhouse gases, LNG, Japan.

ÖZ

Günümüzde karbonsuzlaştırma ve sera gazı (GHG) emisyonlarını azaltma girişimleri nedeniyle sıvılaştırılmış doğal gaz (LNG) alternatif bir denizcilik yakıtı olarak yaygın bir şekilde kullanılmaya başlanmıştır. Japonya en büyük küresel LNG ithalatçısı ve en büyük ham petrol ithalatçılarından biri olduğundan, bu çalışma LNG ve tanker taşımacılığı ile bunların Japonya'daki emisyonlarına ve ithalat hacimlerine odaklanmaktadır. Bu çalışmada, emisyon tahmin modeli Holtrop-Mennen güç tahmin yöntemine dayalı olarak oluşturulmuştur. Otomatik tanımlama sistemi (AIS) verileri kullanılarak yakıt tüketimi ve sera gazı emisyonları tahmin edilmiştir. Daha sonra, Japonya ticaret istatistikleri kullanılarak uzun vadeli sera gazı emisyonu tahmin edilmiştir. Gemi hareket verileri ve ticaret istatistikleri birleştirildiğinde, Japonya'daki sera gazı emisyonunun tankerler için yıllar içinde azalacağı ve LNG taşıyıcıları için sabit kalacağı öngörülmektedir. Sonuçlar çevre ve ticaret politikalarının oluşturulmasında dikkate alınabilir. Çalışmanın Japonya'daki sıfır emisyon projeleri ve uygulamaları için faydalı bilgiler sağlayacağı umulmaktadır.

Anahtar Kelimeler: Otomatik tanımlama sistemi, gemi emisyonu, sera gazları, LNG, Japonya.

Atıf (to cite): *Win, T.K, Watanabe, D. & Toriumi, S.T. (2022). Greenhouse Gas Emissions and Their Trend Prediction Using AIS and Trade Data. Toros University FEASS Journal of Social Sciences, 9(Special Issue),107-121. doi:10.54709/iisbf.1181251*

Makale Geliş Tarihi (Received Date): 28.09.2022 Makale Kabul Tarihi (Accepted Date): 21.11.2022

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1. INTRODUCTION

Transportation including all modes as well as passenger and freight is the second largest CO2 emitter, which accounts for 24% of the world CO2 emissions (International Energy Agency [IEA], 2017). International shipping accounts for 2.89% of the global CO2 emissions in 2018 (International Maritime Organization [IMO], 2021). While shipping is the most efficient and eco-friendly modes of transport in terms of emissions per cargo carried and distance travelled, carbon and greenhouse gas (GHG) emissions are also expected to rise from international shipping (Benamara et al, 2019).

In 2018, IMO adopted the initial strategy on GHG emission reduction from ships. The strategy set the target to reduce the current GHG emissions by at least 40% by 2030, 50% by 2050, and to phase out GHG by the end of the 21st century. UNCTAD (2021) assessed that the global shipping fleet has become more energy efficient although GHG emissions continue to increase (United Nations Conference on Trade and Development).

To achieve the 2050 target and beyond, one of the pathways to GHG reduction will be the use of alternative fuels. Among them, liquefied natural gas (LNG) fuel is one of the options. The (MLIT) assumed that LNG fuels will continue to be the trend to emission pathways (MLIT, 2020) although LNG is not as effective as other alternatives such as hydrogen and ammonia. The IMO report (2020) showed that the LNG market sector will continue to grow. Therefore, this study primarily focuses on LNG shipping and their emissions.

A report by IGU showed that Japan is the top LNG importer, importing 74.43 MT which accounts for 21% of the global LNG market (International Gas Union [IGU], 2021). LNG trade in the Asian market is projected to increase (IEA, 2019). As LNG is already practically applied as alternative marine fuels and as energy use, LNG import to Japan is expected to increase. In addition to LNG, Japan is one of the largest crude oil importing countries. Therefore, it is important to note and keep track of the import volumes and vessels in Japan waters and their GHG emissions. Hence, the Japan coastal region is chosen as a study domain.

In this study, the authors would like to focus on emission status and the relation to crue oil and LNG trade in the Japan coastal region. We hope that the study will offer new insights and considerations in terms of environmental regulations and marine traffic policies to protect the local environment and society.

2. Background on Automatic Identification System (AIS)

Ships of over 300 gross tonnage engaged in international voyages and cargo vessels of over 500 gross tonnage not engaged in international voyages are required to equip Class A AIS by IMO (2002). The purpose of AIS is to enhance safety of life at sea, safety and efficiency of navigation, and protection of the marine environment. Initially intended as a collision avoidance system for vessel identification, target tracking, and information exchange for situational awareness, it is designed for ships to automatically transmit vessel information to ships in vicinity and reporting to maritime authorities.

Nowadays, AIS data provide valuable resources to authorities, academia and industry. AIS data are extensively applied in the following fields: maritime surveillance, environmental sustainability, energy efficiency, speed optimization, route planning and predictive analysis in ship performance and trajectory prediction. Munim et. al. (2020) noted that AIS data applied to investigate a wide range of research topics will contribute to big data and AI research domain in the maritime industry.

In terms of emission study using AIS data, Yao et al (2016) studied ship emission inventories from terrestrial AIS in the Yangtze River estuary. Li et al (2016) investigated uncertainties in ship emission inventory in the Pearl River Delta region. Kim et al (2021) estimated the global LNG fleet emission inventory spatially. Woo and Im (2021) studied the gas emission inventory in Busan by bottom-up approach. Wang et al (2021) conducted the prediction on CO2 emissions by long short-term memory (LSTM). In this study, ship emission estimation will be calculated based on the Holtrop-Mennen power prediction model by using satellite AIS data.

As AIS data are movement data and do not contain cargo information, studies using AIS data focus on emission estimations from marine traffic. However, trade volumes can be estimated from AIS data. Yan et al (2020) analyzed the global marine oil trade based on AIS data. Applying AIS data, the study analyzed the traffic route, trade volume and trade network. Van der Loeff et al (2018) discussed the approach for commodity volume estimation from AIS data by linking cargo composition data, vessel journeys and specifications and vessel emissions from a bottom-up methodology. Trimmer and Godar (2019) suggested a study approach to carbon emissions and air pollution to commodity shipment and allocated emissions to commodities.

3. DATA AND STUDY AREA

3.1. Brief Data Description

The AIS data used in this study were provided by exactEarth. The data are collected via satellites by the company so the data can be obtained throughout the oceans regardless of the vessel position and the weather conditions.The reported data consist of maritime mobile service identity number (MMSI), IMO number, vessel name, callsign, vessel type, vessel type cargo, vessel class, length, width, flag country, destination, estimated time of arrival (ETA), draught, longitude, latitude, speed over ground (SOG) in knots, course over ground (COG), rate of turn (ROT), heading, navigation status, timestamp of the last position and static AIS message, date and time of the last position and static AIS message, main vessel type and sub vessel type. The data were provided in the comma-separated values (csv) format. Each data point is reported in Greenwich Mean Time (GMT).

The data were collected worldwide for 6 months from 2016-01-01 UTC to 2016-06-30 UTC (Universal Time Coordinated). However, not all vessel types and ships were covered by exactEarth satellites as the obtained dataset includes only the following types: oil and chemical tankers, gas tankers, other tankers, tugboats, general cargo ships, offshore vessels, specialized cargo ships, bulk carriers, ro-ro cargo ships, passenger ships, container ships, and others. This dataset extensively focuses on tankers accounting for 98.6%, under which crude oil tankers, oil product tankers, chemical tankers and LNG carriers are sub-categorized.

The trade data used in this study were obtained from the mineral resources and petroleum products statistics report of the Ministry of Economy, Trade and Industry of Japan (METI). The report provides crude oil, petroleum and LNG import and export statistics on a monthly basis and by area and country. In addition to imports and exports, the report consists of the product stock changes, processing and inventory, product value and their trade terms. In this study, monthly import volumes were extracted from import and export section of each products, and they were matched to the vessel types in the AIS data.

3.2. Study Area

In this study, the Japan coastal area is chosen as the main study domain since the authors are mainly interested in estimating GHG emissions in Japan. The United Nations Convention on the Law of the Sea (UNCLOS) Part 2 of "Territorial Sea and Contiguous Zone", in Section 2 "Limits of the Territorial Sea", Article 3 "Breadth of the territorial sea", states that every state has the right to establish the breadth of its territorial sea up to a limit not exceeding 12 nautical miles, measured from baselines determined in accordance with this Convention. Therefore, 12 nautical mile buffers are created along the Japan coastlines and AIS data for 6 months in the buffer zone are selected for analysis.

4. CALCULATING GHG EMISSIONS

4.2. Data Preparation

Before calculation is proceeded, AIS data need to be verified and made reliable. Bereta et al (2021) pointed out technical issues could exist in AIS data: absence of ship identification, human error inputs, reporting frequency, sensor malfunction, and timestamping. Therefore, data processing is mandatory. First, missing ship information in AIS data are either rejected or verified through public vessel tracking services. Then, unusual high speeds are checked, and the vessel positions are confirmed not to be over land. For the next step, transmission timestamp and their intervals are checked as they are not uniform. The data gap was addressed by Goldsworthy (2016) in the spatial-temporal distribution of the ship emission prediction problem. Finally, data are made sure to achieve voyage by voyage emission calculation so that calculations of each vessel voyage do not overlap other voyages. As this study intends to focus on tanker vessel types, only such vessels are filtered in the final dataset. The number of vessels used in the study after buffering is described in the following table.

Table 1. *Number of vessels in the dataset*

Vessel type	Number of vessels (before processing)	Number of vessels (after processing)
Oil and chemical tanker	6974	195
Gas tanker	1318	150
Tug	29	
Other tanker	28	1
General cargo ship	23	
Offshore vessel	16	
Specialized cargo ship	5	
Bulk carrier	24	
Ro-Ro cargo ship	11	
Passenger ship	4	
Container ship	5	
Others	2	
Total	8439	346

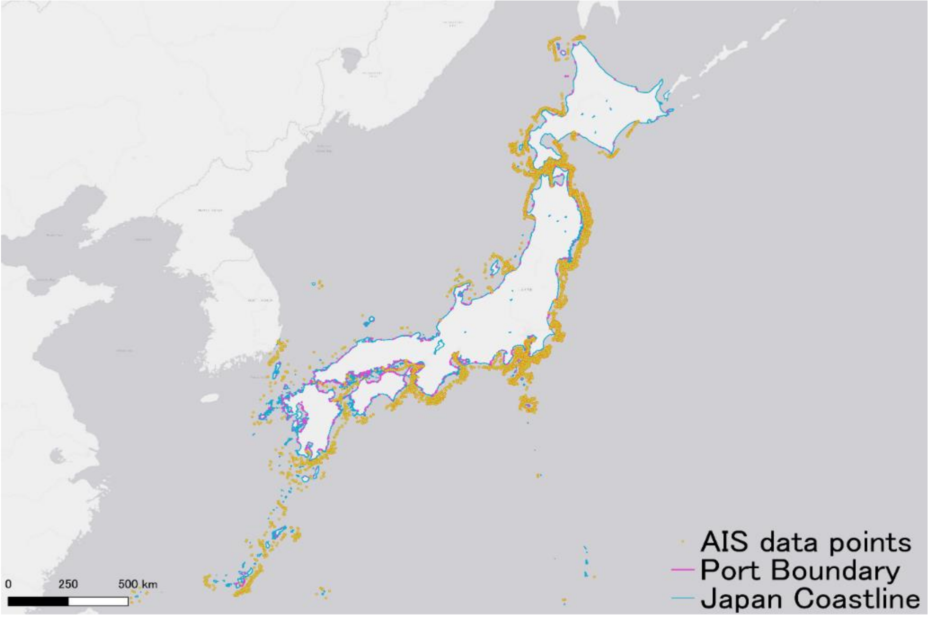

Fig 1*. Study domain and AIS data points*

4.3. Vessel Emission Estimation Model

Once data processing is completed, the vessel emission estimation model will be calculated using ship dimensions, ship resistance, predicted power and assumed parameters. The model is based on International Towing Tank Conference (ITTC) recommended procedures and the approximate power prediction method (Holtrop and Mennen, 1982). The Holtrop-Mennen method is the numerical prediction of propulsive power at the design stage of a ship based on ship dimensions. Holtrop (1984) again re-analyzed resistance and propulsion data, calculated using dimensions and other parameters. The vessel emission estimation method is summarized in Figure 2.

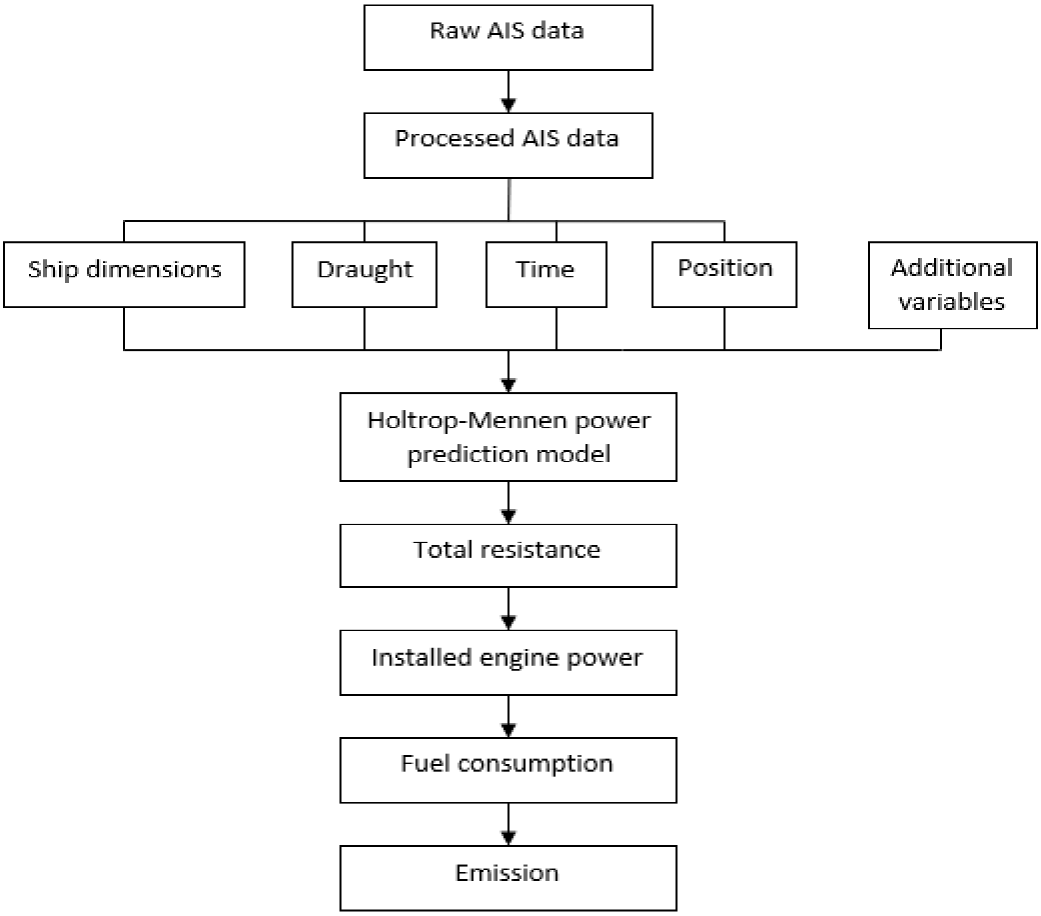

***Fig 2**. Flowchart of vessel emission estimation model*

As AIS data contain length, breadth, and draught, necessary length calculations are carried out first. MAN Diesel & Turbo (2011) assumed average conversions to length of the waterline (LWL) and length between perpendiculars (LPP) from length overall (LOA) which are lengths recorded in AIS data.

$$LPP \; = \; LWL * 0.97 = LOA * (0.97)^2 \tag{1}$$

The displacement (▽) of each vessel can be derived from the following formula.

$$\nabla = C_B * LPP * breadth * draught \tag{2}$$

Approximate block coefficients (CB) of tanker vessels by MAN Diesel & Turbo (2011) range from 0.80-0.85 with average speed of 12-16 knots.

ITTC recommends calculating total resistance of a ship as

$$R_T = 0.5 * C_T * \rho * S * V^2 \tag{3}$$

Where RT represents total resistance, CT for total resistance coefficient, ρ for seawater density, S for wetted surface, V for ship speed.

MAN Diesel & Turbo (2011) assumed residual resistance coefficient to be neglected in the calculations so the equation can be rewritten as

$$C_T = C_F + C_A + C_{AA} + C_R \cong C_F + C_A + C_{AA} \tag{4}$$

Where CF = frictional resistance coefficient, CA = incremental resistance coefficient, CAA = air resistance coefficient, CR = residual resistance coefficient.

An approximate wetted surface estimation is given as follows (Kristensen and Lützen, 2013). Wetted surface calculation can be different depending on ship type as there are different formulations suited to each type of vessel.

$$S = 1.025 * \left(\frac{\nabla}{\text{draught}} + 1.7 * LPP * draught \right) \tag{5}$$

CF can be calculated as follows.

$$C_F = \frac{0.075}{(logR_n - 2)^2} \tag{6}$$

CF and CA can be derived from the following equations.

$$C_A = \frac{0.5 * log(\nabla) - 0.1 * \left(log(\nabla)\right)^2}{1000} \tag{7}$$

Harvald (1983) advised the resistance value will be too low for large ships with displacement more than 160000 T if the above equation is used. In such cases, it is advised to apply the following formula.

$$C_A = Maximum\left(-0.1; \left(0.5 * log(\nabla) - 0.1 * \left(log(\nabla)\right)^2\right)/1000\right) \tag{8}$$

CAA is assumed as follows

***Table 2**. Air resistance coefficients*

Ship Types	CAA
Small, Handysize, Handymax tankers	0.00007
Panamax, Aframax, Suezmax tankers	0.00005
VLCC	0.00004

Source: Kristensen and Lützen (2013)

Reynolds number can be calculated in the following equation, where ν stands for kinematic viscosity of seawater. Kinematic viscosity of seawater can be derived from a study on thermophysical properties of seawater by Nayar et al (2016).

$$R_n = \frac{V * LWL}{\nu} \tag{9}$$

Once total resistance is known, power can be predicted in the below equation (Kristensen and Lützen, 2013). This required power is calculated with vessel's total resistance, sailing at the speed V at calm sea conditions.

$$P = R_T * V * \left(1 + \frac{sea\ allowance}{100}\right) \tag{10}$$

Harvald (1983) suggested sea allowance in power prediction. Sea margin (m), also known as sea allowance, refers to allowances on installed power for roughness, fouling and weather. Depending on ship sizes and hull forms, sea allowance will be different. Small ships will have higher sea allowance while slender hulls will have less service allowance. The suggested sea allowances dependent on shipping routes suggested by Harvald (1983) are taken as approximate parameters in the calculation.

Table 3. *Sea allowance of major shipping routes*

Routes	Sea allowance
North Atlantic, route, westbound	25 – 35 %
North Atlantic, eastbound	20 – 25 %
Europe – Australia	20 – 25 %
Europe - Eastern Asia	20 – 25 %
The Pacific routes	20 – 30 %

Source: Kristensen and Lützen (2013)

Considering resistance, ship speed, sea margin, transmission power (ηD) and quasi-propulsion coefficient (ηT), the installed engine power can be calculated using the following equation (Molland et al, 2011).

$$P_E = \frac{R_T * V}{\eta_D * \eta_T} + m \tag{11}$$

Once estimated power is known, fuel consumption of each vessel can be calculated. Specific fuel oil consumption (SFOC) depends on each ship type as well as marine engines installed onboard. MAN Diesel & Turbo (2011) calculated SFOC for various types of vessels. In this study, only LNG carriers and tankers will be used.

***Table 4**. SFOC by ship type*

Ship type	SFOC in g/kWh
LNG carrier	215
Tanker	210

Source: MAN Diesel & Turbo (2011)

In determining SFOC, engine age also plays a key role. SFOC baselines are proposed for slow/medium/high speed marine diesel engines as shown in the below table.

Table 5. *SFOC by engine age and type*

Engine age	SSD	MSD	HSD
Before 1983	205	215	225
1984-2000	185	195	205
Post 2001	175	185	195

Source: IMO GHG Study Report (2021)

Fuel consumption is given by the following equation, where SFOC is in g/kWh and time difference in hours (ΔT)

$$Fuel\ consumption\ (FC) = P_E * SFOC * \Delta T \tag{12}$$

Vessel emission value can be derived from emission factors of each pollutant.

$$Emission = Emission\ factor * FC \tag{13}$$

Depending on fuel types, the emission factor of the pollutant will vary and their values were introduced in IMO GHG Reports (2014 and 2021).

Table 6. *Emission factors*

Pollutant	Emission Factor (g/g fuel)
Carbon dioxide (CO2)	3.114
Nitrogen oxides (NOX)	0.0903
Sulphur oxides (SOX)	0.025
Particulate matter (PM)	0.00728
Carbon monoxide (CO)	0.00277
Methane (CH4)	0.00006
Nitrous oxide (N2O)	0.00015
Non-methane volatile organic compounds (NMVOC)	0.00308

Source: IMO GHG Reports (2014).

5. RESULTS

5.2. Fuel Consumption and GHG Emissions

Based on the AIS data and the power prediction method, fuel consumption and GHG emissions in the Japan coastal waters for the first six months of 2016 can be calculated. Fuel consumption is calculated to be 150,041.02 tons.

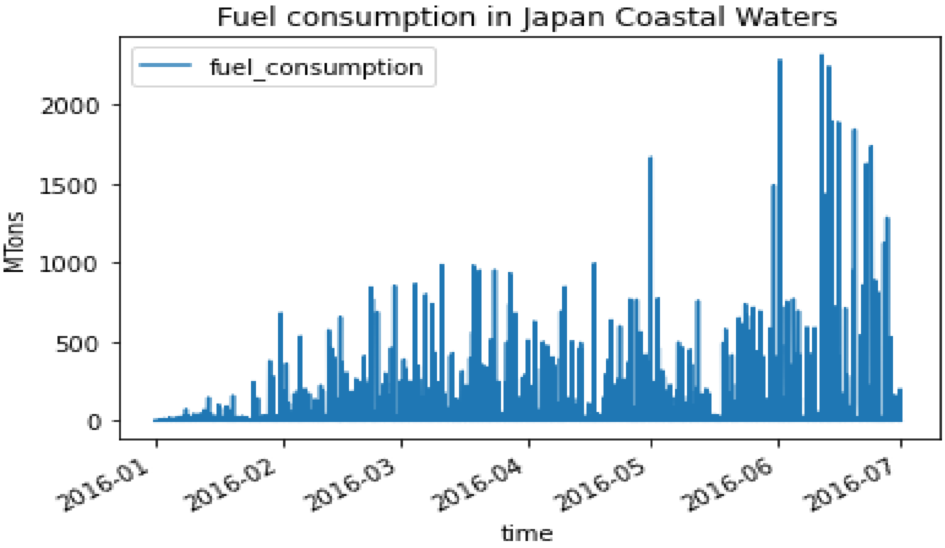

Fig 3. *Daily fuel consumption in Japan coastal waters*

Using the emission factors of each pollutant, the emission inventory can be estimated. The calculated results are shown in the following table and their daily amounts in the below figure. In the emission inventory, CO2 pollutes the most, 96% of the total emission.

Table 7. *Emission inventory for 6 months*

Emission Pollutant	**Amount (metric tons)**
CO2	467,227.76
NOx	13,548.70
SOx	3,751.02
PM	1,092.29
CO	415.61
CH4	9.00
N2O	22.50
NMVOC	462.12

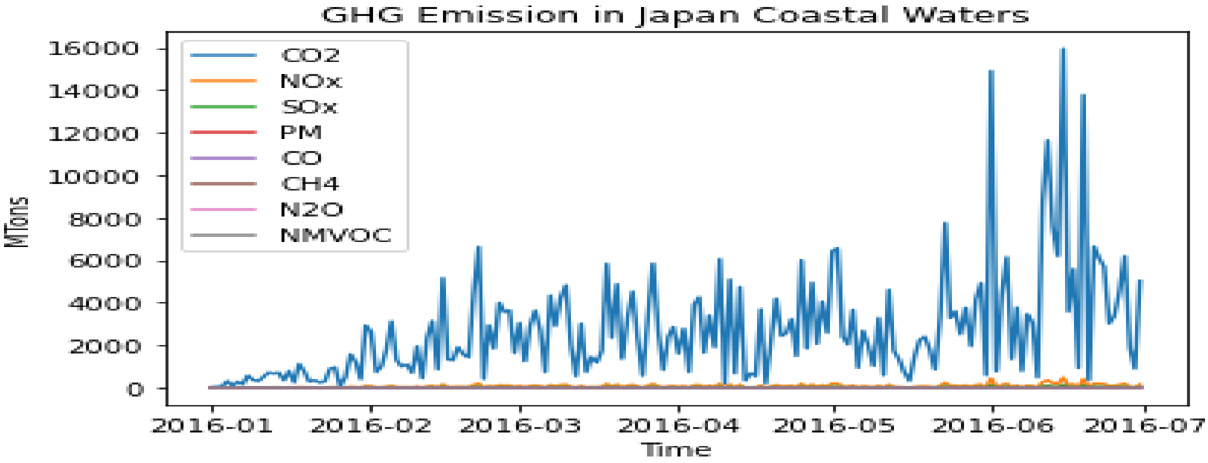

Fig 4. *Daily emissions in Japan coastal waters*

5.3. Long Term GHG Emission Prediction

The Ministry of Economy, Trade and Industry of Japan (METI) compiles the trade statistics of monthly LNG, crude oil and fuel products import amount. The mode of transport to import energy sources such as fuel, oil and LNG is via tanker ships. In addition, 32 LNG receiving terminals (19% of the global share) are in Japan (IGU, 2021). Therefore, energy import volumes and ship emission volumes are important factors to consider for long term prediction. The prediction can be applied in policy making for energy resource import and environmental protection.

Referring to the 2016 METI statistics from January to June, total LNG import is 38,543,894 tons and the average is 6,423,982 tons a month. For fuel and oil products, the import volume is 15,184,603 kiloliters (kl), averaging 2,530,767 kl per month.

Table 8*. Monthly imports and emissions (2016 January to 2016 Jun)*

Import		**Emission**							
Oil & fuel	**LNG**	**CO2**	**NOx**	**SOx**	**PM**	**CO**	**CH4**	**N2O**	**NMVOC**
kl	**MTon**	**MTon**							
3419728	6571013	17469.38	506.5784	140.2487	40.84043	15.53956	0.336597	0.841492	17.27864
2595435	7022133	62450.04	1810.931	501.3651	145.9975	55.55125	1.203276	3.008191	61.76818
2324958	7830571	83793.52	2429.851	672.7161	195.8949	74.53695	1.614519	4.036297	82.87863
2474860	6113092	76471.08	2217.514	613.9296	178.7763	68.0234	1.473431	3.683578	75.63613
2430470	5337500	79509.95	2305.635	638.3265	185.8807	70.72658	1.531984	3.829959	78.64183
1939152	5669585	147533.8	4278.196	1184.44	344.9088	131.2359	2.842655	7.106637	145.923

Referring to Table 8 and Figure 3, import volumes tend to decrease in June 2016 whereas emission volumes tend to be higher than previous months. Ship emissions tend to increase steadily from January 2016 and remain mostly stable from March to May 2016.

Using the METI statistics, vessel GHG emission results and vessel arrivals in Japan, long term GHG emission is predicted. The trend shows that energy resources are imported in high quantities in the beginning and ending of each year and start decreasing around March every year. However, LNG imports drop sharply from March 2020 to 4224784 tons in May 2020 while the average per month is 6276284.667 tons. This is illustrated in Figure 5.

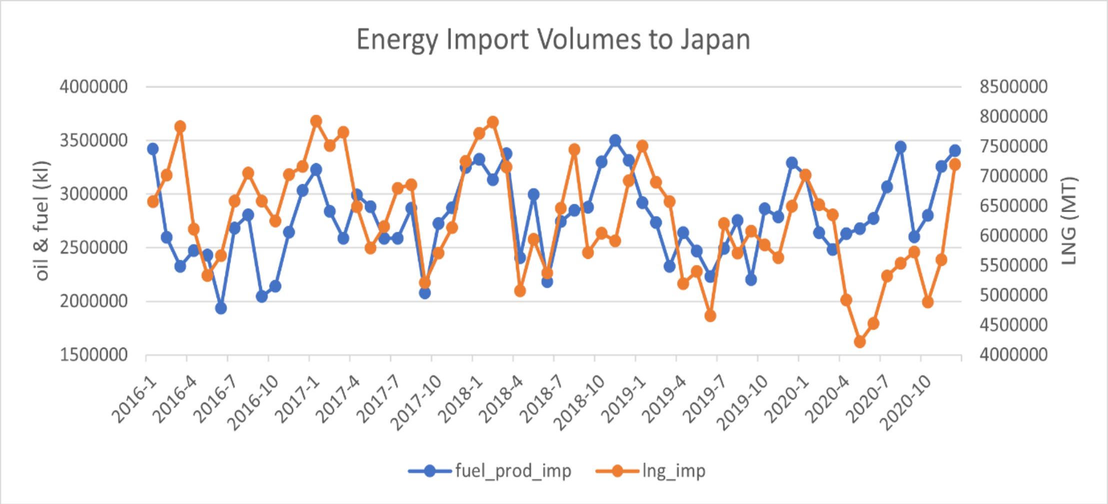

Fig 5*. Energy import to Japan (2016 ~ 2020).*
Source: *METI.*

In addition to trade statistics from the Japan METI agency, UN Comtrade database is also used. The database aggregates global trade statistics annually and monthly by product and trading partner. Among the UN Comtrade databases, the AIS-based database is applied in this study. It estimates the global seaborne trade in real time by collecting AIS data. The data is updated on a weekly basis. The trade data derived from AIS data include the number of port calls, metric tons of cargo, deadweight tonnage by specifying the reporting country, vessel type, trade flows: import or export, and the period.

In order to predict GHG emissions from LNG carriers and tankers in Japan coastal waters, fuel consumption is estimated first by the following variables: fuel oil and products import volumes, LNG import volumes, port calls, and deadweight tonnage from the dataset. The number of port calls and deadweight tonnage derived from the Comtrade database and those derived from the exactEarth AIS dataset are compiled and checked on the differing values. Port calls refer to the number of times a vessel calls at a port to carry out cargo loading and discharging operations. Deadweight tonnage refers to a vessel's weight carrying capacity, not including the empty weight of the ship. Then emission factors are applied to predict the total emission volumes for each type of vessel separately as in the equation (13).

$$Fuel\ consumption\ LNG = \alpha_1 * LNG\ import + \alpha_2 * port\ call + \alpha_3 * deadweight \tag{14}$$

$$Fuel\ consumption\ tanker = \beta_1 * \text{oil import} + \beta_2 * \text{port call} + \beta_3 * \text{deadweight} \tag{15}$$

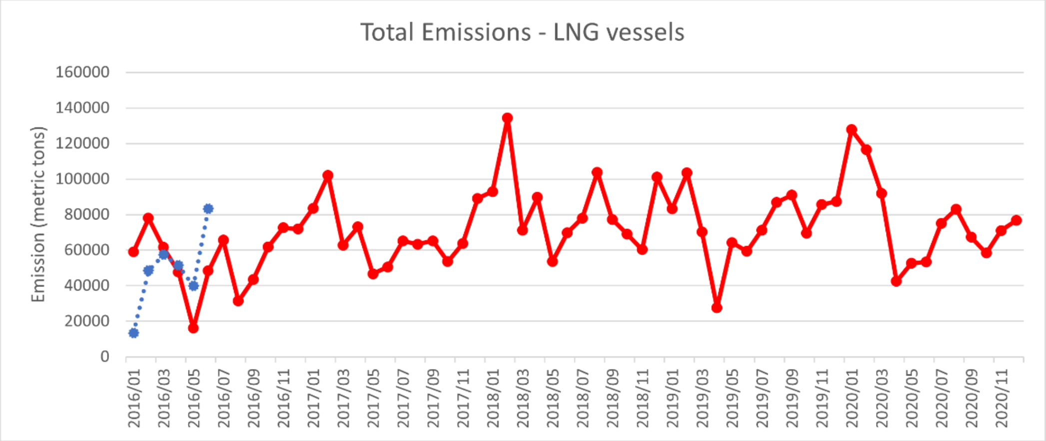

Fig 6. *Projected emissions from LNG carriers*

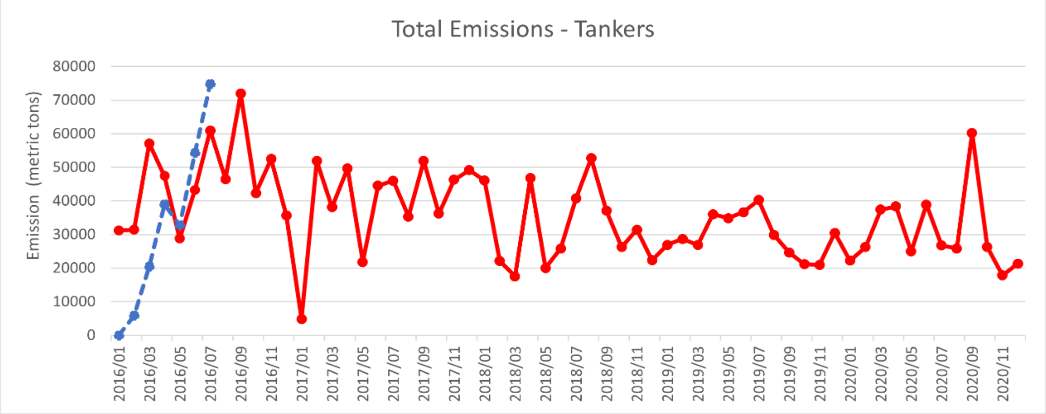

Fig 7. *Projected emissions from tankers*

In Figures 6 and 7, the blue line represents the estimated emissions from the AIS data for six months while the red line represents projected emissions based on the METI trade statistics and UN Comtrade database. In this study, estimations were made to compare emission volumes for 6 months and long term predictions based on the trend of 6 months were carried out. The 6-month comparison result discovered that high differences occur in the first month of study, where emissions estimated from trade data were 4 times higher for tankers and 3 times higher for LNG carriers than emissions calculated from AIS data; emissions from AIS data were found to gradually increase in the remaining 5 months of comparison. During January 2016 to June 2016, total emissions estimated from the trade were found to be higher than from AIS data (24% for tankers and 28% for LNG carriers). Similar trends were discovered in both AIS and trade data. In the long term perediction, although the import trend and the volumes remain relatively stable from 2016 to 2020, overall GHG emissions tend to gradually decline from 2016. The decline is mostly found in tankers as the vessels increase in size and utilize more space since the deadweight gets larger and fewer port calls are made. However, LNG carriers' emissions remain almost the same and projected to increase.

6. CONCLUSION

In this study, two main objectives are focused: GHG emission estimations from tankers and LNG carriers and trade statistics. Emission from 8 air pollutants (CO2, NOx, SOx, PM, CO, CH4, N2O and NMVOC) is calculated for the first half of 2016.

Based on ITTC procedures and the Holtrop-Mennen numerical power prediction method, vessel emission estimation model estimates the GHG emissions of LNG and tanker ships in Japan coastal waters from the AIS data. As tracking data do not cover all ships, calculated emissions will not cover the actual emissions. In the dataset, engine types and their information are not available. Therefore, calculations are done with value assumption. If more information is available, better accuracy in fuel consumption and emissions can be estimated. With the calculation results from the current AIS data, it is assumed that emissions are particularly higher after the peak season, particularly during the third quarter of each year. This can be due to the higher vessel movements once energy resources are imported. Therefore, air pollution impacts on the local environment and urban and port areas should be investigated. It can help the government and stakeholders identify environmental and health issues to improve the local society.

Next, the long term GHG emission is predicted based on the trade data. The prediction results show the gradual decrease in GHG over years. However, this prediction is based on the available six-month vessel movement data. In addition, prediction in this study is based only on statistics from two sources: Japan METI and UN Comtrade. Further study should be focused to develop a better emission forecast model using more trade data. In this study, emission estimation from trade data is studied based on vessel port calling activity and cargo weight carried. From this study, vessel emissions can be estimated if the country's trade volumes are known. The authors recognize that the prediction model can be improved and re-evaluated provided that more historical AIS data are available. Further research should be conducted on more accurate data-driven approaches to estimate ship emissions from each trade and commodity so that environmental friendly trade policy can be further researched and implemented to benefit the local society.

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