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Developing an AIS Big Data-Driven Framework for Ship Emission Monitoring in Ports

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ABSTRACT

The rapid expansion of maritime transportation has significantly impacted air quality due to increased ship emissions. This study aims to develop a ship emission monitoring system utilizing Automatic Identification System (AIS) big data, with Tanjung Priok Port in Indonesia (ID TPP) as the case study. The system is designed to monitor and analyze ship emissions based on historical AIS data, providing actionable insights to mitigate environmental impacts. By integrating various data processing techniques, including data preprocessing, database development, sailing time and speed calculation, and emission estimation, this research provides a comprehensive framework for a ship emission monitoring system. The system can be implemented in ports through the development of an interactive web-based dashboard, enhancing the decision-making capabilities of port authorities and other stakeholders. The results demonstrate the system's potential for effectively monitoring emissions and promoting sustainable maritime operations.

1 Introduction

Over the past few decades, the substantial growth of maritime transportation has exerted a significant impact on air quality. Approximately 90% of global traffic is transported by sea, contributing significantly to environmental pollution. Studies show that ships emit various pollutants into the atmosphere, including NO_x, CO_2, volatile organic compounds, SO_x, and particulate matter. Ships account for 2.2% of global CO_2 emissions and a large percentage of NO_x and SO_2 emissions. The shipping industry contributes approximately 1.056 billion tons of CO2 annually, accounting for 2.9% of global greenhouse gas emissions. This amount is projected to rise substantially over the next 10 to 40 years, driven by the anticipated growth in international trade activities [1], [2].

These pollutants contribute to adverse health effects, environmental degradation, and reduced air quality in densely populated coastal areas [3], [4], [5], [6], [7]. Previous studies have shown that shipping emissions directly impact around 230 million people globally. In 2016, East Asia experienced over 24,000 premature deaths annually attributed to these emissions [8]. Without intervention, shipping-related pollution could increase by 150 to 250% globally by 2050, posing greater health risks to the public [9], [10]. About 70% of ship emissions occur within 400 km of the coast, significantly impacting air quality in coastal and urban areas. High ship traffic in ports degrades air quality, highlighting the need for detailed ship emission inventories and continuous monitoring to support effective management strategies [11].

Many researchers have used the Ship Traffic Emission Assessment Model (STEAM) with Automatic Identification System (AIS) big data to estimate ship emissions in ports. AIS big data refers to the large-scale collection, processing, and analysis of AIS signals transmitted by ships worldwide. AIS is a maritime communication sys-

tem used for vessel tracking and collision avoidance, and its data contains valuable information about ship movements. The activity-based method calculates emissions by identifying ship activities and their respective emission factors, offering detailed statistical analysis of emission sources. For example, research demonstrated that STEAM could accurately estimate emissions from maritime traffic by integrating AIS data with ship engine characteristics and fuel consumption rates [12]. More recently, research highlighted the importance of real-time AIS data processing for monitoring emissions in dynamic port environments, showing that delays in data handling could lead to significant underestimations of short-term emission spikes [13]. However, real-time AIS data processing remains crucial for timely monitoring and management of pollution.

AIS enhances navigation safety and communication among ships by providing real-time static and dynamic data. Despite its benefits, processing AIS data requires significant effort to ensure accuracy and efficiency in real-time emission assessment. For instance, some studies emphasized that AIS-based emission models must account for data gaps, errors, and inconsistencies to produce reliable estimations. Meanwhile, a research demonstrated that real-time AIS data processing could significantly improve the temporal resolution of ship emission monitoring, allowing for more responsive environmental management [14]. These findings highlight the need for robust data processing techniques to maximize the potential of AIS in emission assessments.

Although there has been extensive research on ship emission monitoring systems, this study differs by focusing on Tanjung Priok Port in Indonesia (ID TPP). As a major hub in the Southeast Asia region, this port is crucial for the national economy and significantly impacts environmental quality. This research aims to develop a real-time ship emission monitoring system using AIS data by employing Python programming and the Django framework. Django serves as the backbone of the web-based system, handling data processing, database management, and real-time visualization through an interactive dashboard. By integrating Django with a MySQL database and AIS data processing scripts, the system enables automated emission calculations and provides critical data for policymakers to effectively mitigate environmental impacts. This study also addresses challenges such as mapping zone accuracy, data collection periods, and data visualization.

2 Materials and Methods

2.1 Identification of Ship Trajectories

The process of identifying ship trajectories is conducted to determine the direction of ship movement when entering the Port area. This identification process uses AIS data variables that have undergone preprocessing. Maritime Mobile Service Identity (MMSI) and International Maritime Organization (IMO) data are used to identity each ship. MMSI is used because it has a unique identification system for each ship and is automatically registered in the AIS data (while the IMO number must be manually entered by the crew, allowing for potential errors). Longitude and latitude data are then used to determine the coordinates of the ship on the map. Latitude and longitude are measured based on Earth's coordinate parameters, making them accurate indicators of the ship's position. The final data used is the timestamp data, which indicates the time the AIS data was collected.

Using a combination of these AIS data, the ship's trajectory or path can be constructed based on the collected timestamps. This trajectory can be used to identify the ship's position and how long it remained in that position. Additionally, the ship's trajectory can be calculated to determine its speed.

As shown in Figure 1, the sampling period is structured over designated time intervals, enabling the acquisition of AIS data streams in continuous data blocks. Within each block, ship trajectories are extracted initially for various vessels. Given the essential role of Maritime Mobile Service Identity (MMSI) in uniquely identifying individual ships, AIS messages containing the same MMSI within a data block can be consolidated.

2.2 Ship Traffic Emission Assessment Model (STEAM)

The Ship Traffic Emission Assessment Model (STEAM) was developed by Jalkanen [12] as a framework to measure and analyze emissions from maritime traffic. By collecting data on ship movements, fuel consumption, and engine characteristics, STEAM provides accurate emission estimates. Considering various pollutants such as CO_2, NO_x, SO_x, and particulate matter (PM), The STEAM model facilitates a deeper understanding of the environmental impacts associated with maritime activities. STEAM is a crucial tool for researchers and policymakers to formulate emission mitigation strategies in the shipping sector.

STEAM is an estimation model that assesses emissions based on input data such as ship activity, engine specifications, and emission factors. This method has been successfully applied in Various studies that provided insights that support global decision-making processes [15], [16], [17]. Figure 2 presents the STEAM model framework, which relies on data from multiple sources. These include Lloyd's List Intelligence for information on the power and tonnage of heavy equipment, as well as Automatic Identification System (AIS) data for tracking ship types, sailing durations, and speeds. Additionally, empirical values from prior research are utilized for correction factors and emission coefficients.

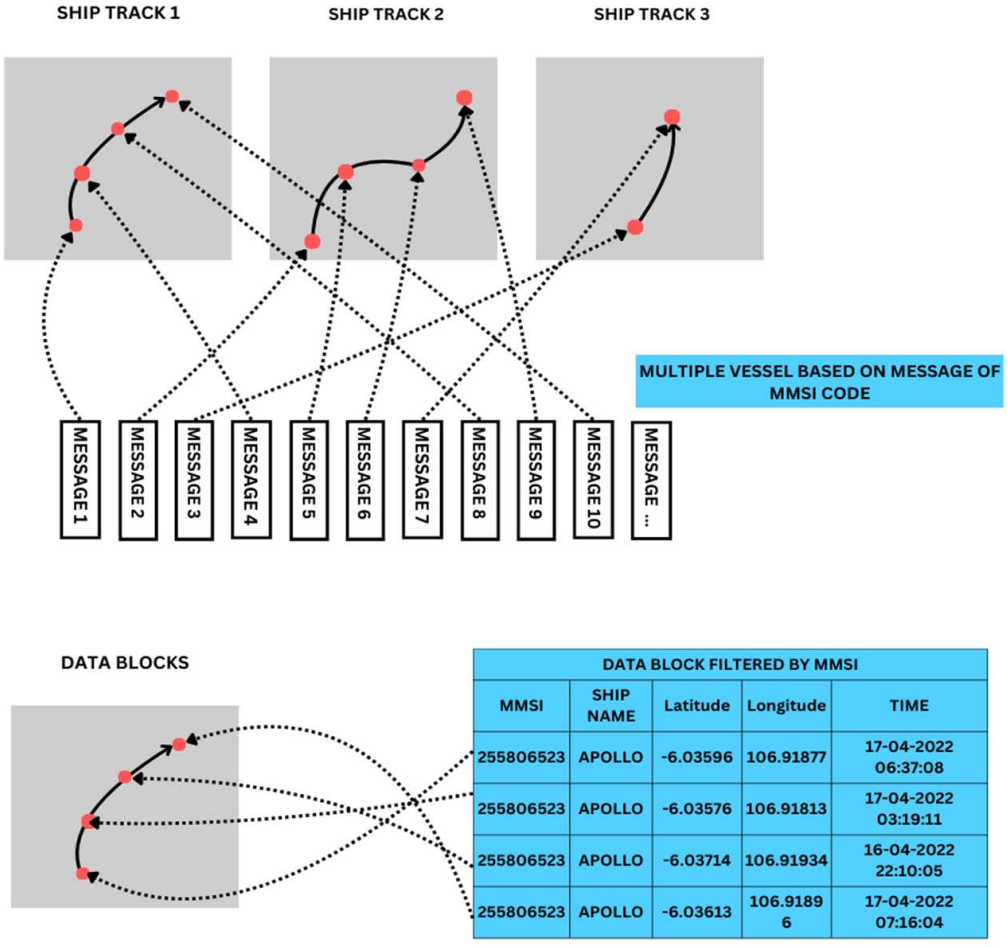


Figure 1 AIS Data Stream Splitting

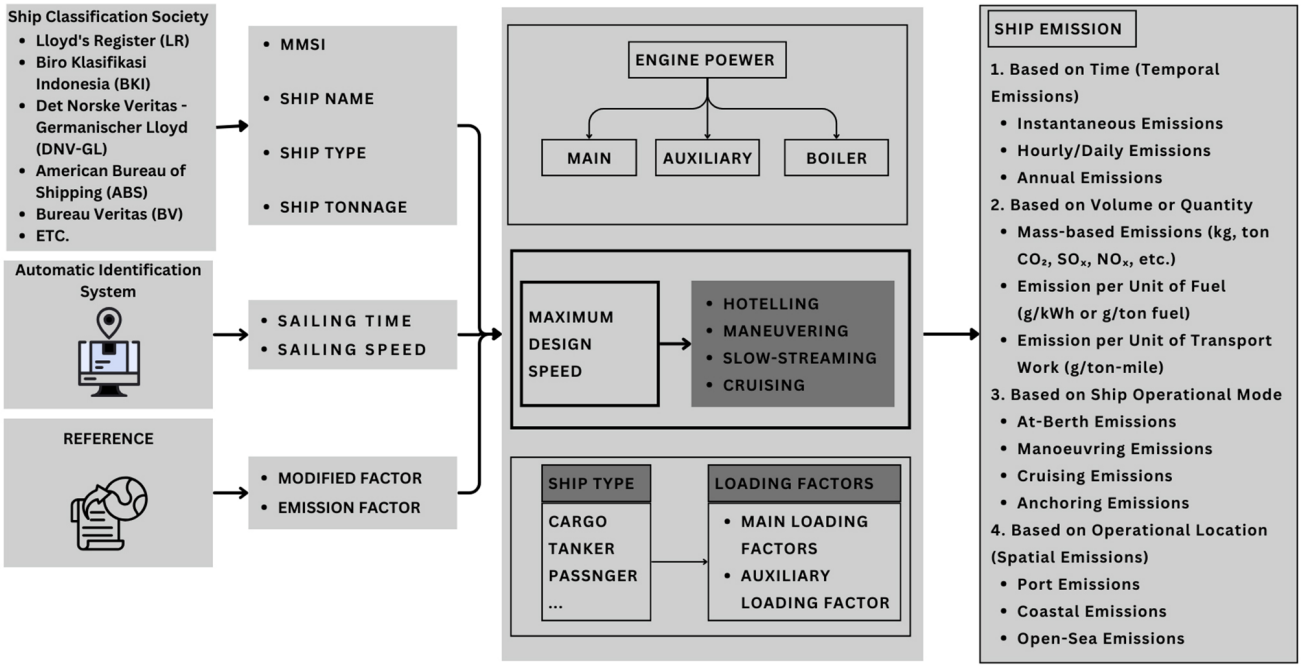


Figure 2 STEAM Method Flow

The diagram in Figure 2 highlights key components of the STEAM method, including inputs like the ship's main engine power, auxiliary engine power, and tonnage, which influence the calculation of maximum design speed. These inputs are critical for determining emission factors, which are adjusted using data from Lloyd's databases, AIS data, and reference values.

Studies such as [18] have emphasized the importance of integrating data sources to ensure accurate emission assessments. Different types of ships have varying power levels, directly affecting their emissions. Generally, ships utilize three primary power sources: main engines, auxiliary engines, and boilers [19]. Emissions from these engines can be estimated using specific equations 1 – 3 outlined in the literature [16], [20].

Main Engine:

$$E_{a,i} = (P_a \times L_a \times T_a \times E_{Fa})/10^3 \quad (1)$$

Auxiliary Engine:

$$E_{b,i} = (P_b \times L_b \times T_b \times E_{Fb})/10^3 \quad (2)$$

Boiler:

$$E_{c,i} = (P_c \times E_{Fc} \times T_c)/10^3 \quad (3)$$

The notation description of the formula is explained as presented in Table 1.

Table 1 Notation description of the emissions from different engines equation

Notation	Description
i	The type of pollutant emitted, including CO, CO_2, NMVOC, NO_X, $PM_{2,5}$, SO_2
$E_{a,i}$	The emission of the ship's main engine for different pollutants (units: Kg)
$E_{b,i}$	The emission of the ship's auxiliary engine for different pollutants (units: Kg)
$E_{c,i}$	The emission of the ship's boiler for different pollutants (units: tone)
p_a	Ship's power for Main Engine (units: kW)
p_b	Ship's power for Auxiliary Engine (units: kW)
p_c	Ship's power for Boiler Engine (units: kW)
L_a, L_b	The load factor for the main and auxiliary engines, where the value is obtained from the actual speed and the ship's maximum speed: $L = V_{act} / V_{max}$; V_{act} indicates the actual speed; V_{max} indicates the maximum speed
EF_a	The emission factor of the main engine (units: g/kWh)
EF_b	The emission factor of the auxiliary engine (units: g/kWh)
T_a	Operating time of the main engine (unit: hours)
T_b	Operating time of the auxiliary engine (unit: hours)
T_c	Operating time of the boiler (unit: hours)

Table 1 presents the notation used in ship emission calculations, detailing various pollutants such as CO, CO_2, NOX, and SO_2. It defines emissions from different sources, including the main engine, auxiliary engine, and boiler, along with their respective power outputs. The table also introduces load factors for the main and auxiliary engines, calculated based on the ratio of actual speed to maximum speed. Furthermore, it includes emission factors specific to each engine type, which are essential for accurately assessing and quantifying ship emissions.

2.3 Load Factor

The load factor for the main engine (ME) is calculated using the Propeller Law, as defined by the Port of Long Beach [21], and is expressed by the following equation 4.

$$LF = \left(\frac{AS}{MS}\right)^3 \quad (4)$$

In this equation, LF represents the load factor of the main engine, AS is the actual operating speed (knots), and MS denotes the maximum speed (knots). The maximum speed data for each ship is obtained from sources such as Lloyd's database, the CCS database, or prior research and surveys, while the actual speed is calculated by dividing the distance traveled between two AIS-reported positions by the time interval between them.

Within the STEAM model, the emission factor varies based on changes in the load factor of the main engine [22], [24], [25]. Specifically, when the load factor is below 20%, a correction factor is applied to the emission factor, as shown in Table 2. For auxiliary engines, the load factor is based on the ship's type and activity, as shown in Table 3.

2.4 Ship Emission

Ship emissions refer to the release of various pollutants into the air resulting from the operational activities of sea vessels. These pollutants are produced during the fuel combustion process in ship engines. Types of ship emissions involve harmful gases and particles that can affect air quality around water areas and significantly contribute to environmental impact.

The primary types of ship emissions are categorized and shown in Table 4. The emission factors used in this study are derived from previous ship emission inventories [16].

Table 2 Emission Correction Factor for Main Engine at Low Load [22]

Load	SO_2	NO_x	PM	NMVOC	CO	CO_2
0.01	1.00	11.47	19.17	59.28	19.32	1.00
0.02	1.00	4.63	7.29	21.18	9.68	1.00
0.03	1.00	2.92	4.33	11.68	6.46	1.00
0.04	1.00	2.21	3.09	7.71	4.86	1.00
0.05	1.00	1.83	2.44	5.61	3.89	1.00
0.06	1.00	1.60	2.04	4.35	3.25	1.00
0.07	1.00	1.45	1.79	3.52	2.79	1.00
0.08	1.00	1.35	1.61	2.95	2.45	1.00
0.09	1.00	1.27	1.48	2.52	2.18	1.00
0.10	1.00	1.22	1.38	2.20	1.96	1.00
0.11	1.00	1.17	1.30	1.96	1.79	1.00
0.12	1.00	1.14	1.24	1.76	1.64	1.00
0.13	1.00	1.11	1.19	1.60	1.52	1.00
0.14	1.00	1.08	1.15	1.47	1.41	1.00
0.15	1.00	1.06	1.11	1.36	1.32	1.00
0.16	1.00	1.05	1.08	1.26	1.24	1.00
0.17	1.00	1.03	1.06	1.18	1.37	1.00
0.18	1.00	1.02	1.04	1.11	1.11	1.00
0.19	1.00	1.01	1.02	1.05	1.05	1.00
0.20	1.00	1.00	1.00	1.00	1.00	1.00

Table 3 Auxiliary Engine Load Factor Assumptions [23]

Ship Type	Sailing	Manoeuvring	Mooring
Auto carrier	0.13	0.67	0.24
Bulk carrier	0.17	0.45	0.22
General cargo	0.17	0.45	0.22
Tanker	0.13	0.45	0.67
Container	0.13	0.5	0.17
Reefer	0.20	0.67	0.34
Passenger	0.80	0.8	0.64
Ro-ro	0.15	0.45	0.3
Rest	0.17	0.45	0.22

Table 4 Ship Emission Description

Pollutant	Description	Impact
NO_x (Nitrogen Oxides)	Irritant gases, including NO and NO_2, are produced from high-temperature fuel combustion.	Causes respiratory issues, acid rain, and smog formation.
PM_{10}, $PM_{2.5}$ (Particulate Matter)	Fine particles with diameters ≤10 μm or ≤2.5 μm. Emitted from fuel combustion and engine wear.	It can penetrate human lungs, causing respiratory and cardiovascular diseases.
CO (Carbon Monoxide)	Produced from incomplete combustion of fossil fuels.	Harmful to human health; reduces oxygen delivery in the bloodstream.
SO_x (Sulfur Oxides)	Formed from burning sulfur-containing fuels, primarily HFO (Heavy Fuel Oil).	Causes respiratory and cardiovascular issues; contributes to acid rain.
NMVOC (Non-Methane Volatile Organic Compounds)	Organic compounds emitted from fuel evaporation and combustion.	Contributes to ground-level ozone and secondary pollutant formation.
CO_2 (Carbon Dioxide)	The main greenhouse gas emitted from fuel combustion.	A major contributor to global warming and climate change.

Table 5 Emission Factors Based on Machine Type and Pollutant Type

Machine Type	Engine Type	Emission Factors (E_F, g/kWh)					
		CO_2	NO_x	CO	NMVOC	PM	SO_2
ME	SSD	620.00	17.00	1.40	0.632	1.39	10.50
ME	MSD	683.00	13.00	1.10	0.527	1.39	11.50
ME	HSD	686.00	12.70	1.00	0.527	1.39	11.31
AE	MSD	683.00	13.00	1.10	0.421	1.39	12.30
Boiler	-	970.00	2.10	0.20	0.105	0.57	16.50

Table 6 Ship Main Activities and Emission Equations [16]

Operation Modes	Matching	Emission Formula
Hoteling	$< 1kn$	$E = E_b + E_c + E_p$
Anchoring	$1kn - 3kn$	$E = E_b + E_c$
Manoeuvering	$3kn–8kn, < 20\%MCR$	$E = E_a + E_b + E_c$
Slow-steaming	$8kn - 12kn, 20\%MCR–65\%MCR$	$E = E_a + E_b$
Cruising	$> 12kn, < 65kn$	$E = E_a + E_b$

Note that the values presented are energy-based emission factors (expressed in g/kWh). Most of the CO_2 emission factors are derived by multiplying the Specific Fuel Consumption (SFC) of each engine type with the corresponding fuel-based emission factors (in g CO_2/g fuel). Similarly, SO_2 emission factors are determined based on the sulfur content of the fuel used.

These emission factor values are sourced from the Fourth IMO GHG Study 2020 and reflect the standard parameters adopted for various engine types, including slow-speed diesel (SSD), medium-speed diesel (MSD), high-speed diesel (HSD), auxiliary engines, and boilers.

2.5 Ship Activity Identification

When a ship is sailing, accelerating, or decelerating, its engines operate under varying conditions, including fuel consumption and engine performance, to generate the necessary power for movement. Consequently, emissions from ship engines differ depending on the ship's activity. Identifying various ship activities using AIS data is crucial for calculating ship exhaust emissions.

A ship is considered to be sailing if its speed exceeds 3 knots (1 knot = 1.852 km/h). This threshold distinguishes whether a ship is actively in motion or stationary. When sailing under typical operational conditions, a ship's instantaneous speed generally corresponds to approximately 85% of its engine's maximum capacity, as supported by operational data and modeling studies. [26]. AIS data shows that ships in motion generally exceed speeds of 12 knots. In contrast, manoeuvring speeds typically range between 3–8 knots, as vessels adjust their speed and direction when navigating into or out of ports, coastal waters, or areas with restricted visibility.

In the STEAM methodology, emission factors can vary according to fluctuations in the main engine load factor [17], [27].

Essentially, the Maximum Continuous Rated Engine Power (MCR) serves as the primary parameter representing the main engine load factor, as shown in Table 6.

2.6 Linear Regression Analysis to Determine Ship Power

The estimation of main engine power plays a crucial role in ship performance analysis and emissions assessment. However, due to data incompleteness in the current dataset, especially regarding power ratings, a direct regression modeling approach was not feasible. Therefore, this study adopted empirically validated regression equations developed in previous research to estimate main engine power based on ship dimensions.

Prior studies have shown a strong correlation between main engine power and the product of ship length and breadth, especially for cargo ships and tankers [14]. As a result, the present work utilizes existing polynomial regression models that relate engine power (kW) to the projected area of the hull (length × breadth, in m^2). The equations (5) and (6) represent the power estimation models for cargo ships and tankers, respectively.

Cargo:

$$y = 7.52 \times 10^{-5} x^2 + 0.59x - 41.48 \quad (5)$$

Tanker:

$$y = 3.32 \times 10^{-5} x^2 + 0.27x - 57.20 \quad (6)$$

where x represents the product of the ship's length and width (m^2) and y represents the ship's main engine power (kW).

This methodology provides a robust estimation technique for determining main engine power based on ship dimensions, which can be effectively utilized in ship performance assessments and emission monitoring systems [28].

The ratio of auxiliary engine power to main engine power varies depending on the type of ship. For example, car carriers have a ratio of 0.266, while bulk carriers, ocean tugs, and other unspecified ship types share a similar ratio of 0.222. Container ships exhibit a slightly lower ratio of 0.220, whereas cruise ships have a higher ratio of 0.278. General cargo ships demonstrate the lowest ratio at 0.191, while refrigerated ships have the highest ratio at 0.406. Roll-on ships show a ratio of 0.259, and tankers have a ratio of 0.211. These ratios are used to calculate the auxiliary engine power based on the ship's main engine power[16] .

2.7 Design Speed

After determining the main engine power, it becomes possible to estimate the ship's design speed if it is not already known. This estimation relies on a regression model that correlates the design speed with the total engine power, particularly for tankers, container ships, and bulk carriers. For tankers and cargo vessels, the total main engine power can be derived using Equation 7 [28].

$$\begin{cases} CR = \alpha * DWT^{\beta} * V^{\gamma}, & Mtanker \\ CR = \alpha * TEU^{\beta} * V^{\gamma}, & cargo \end{cases} \quad (7)$$

Where MCR represents the total main engine power (measured in kilowatts) [kW], DWT denotes the deadweight tonnage of the tanker (in tons) [t], TEU indicates the number of containers, V refers to the design speed (in knots), and α, β, γ are the coefficients used in the regression model.

Using Equation 7, the design speed is determined inversely based on the calculated engine power. The resulting predictive formula for estimating the design speed of tankers and cargo vessels is provided in Equation 8.

$$\begin{cases} V_T = \sqrt[0.6]{MCR_T/2.66DWT^{0.6}}, & tanker \\ V_C = \sqrt[0.6]{MCR_T/4.297DWT^{0.6}}, & cargo \end{cases} \quad (8)$$

2.8 Methods

Ship Traffic Emission Model is a framework used to measure and analyze emissions produced by ships during sea operations. This model helps in understanding the environmental impact of shipping activities by calculating the number of emissions generated by various pollutants such as CO_2, NO_x, SO_x, and others [30].

The research method used in this study is inspired by the Ship Traffic Emission Model. However, there are important differences in the approach taken by the author. First, the author performs data preprocessing to clean raw data for easier processing. Then, to identify ship trajectories, the author uses a simple equation to determine sailing speed and time. Finally, the output of this research will be a website that displays processing results automatically in an integrated process. With this approach, the author hopes to provide a more efficient and accessible solution for stakeholders in understanding and controlling the environmental consequences of shipping practices.

The development flow of the ship emission monitoring system is illustrated in Figure 3, starting with the col-

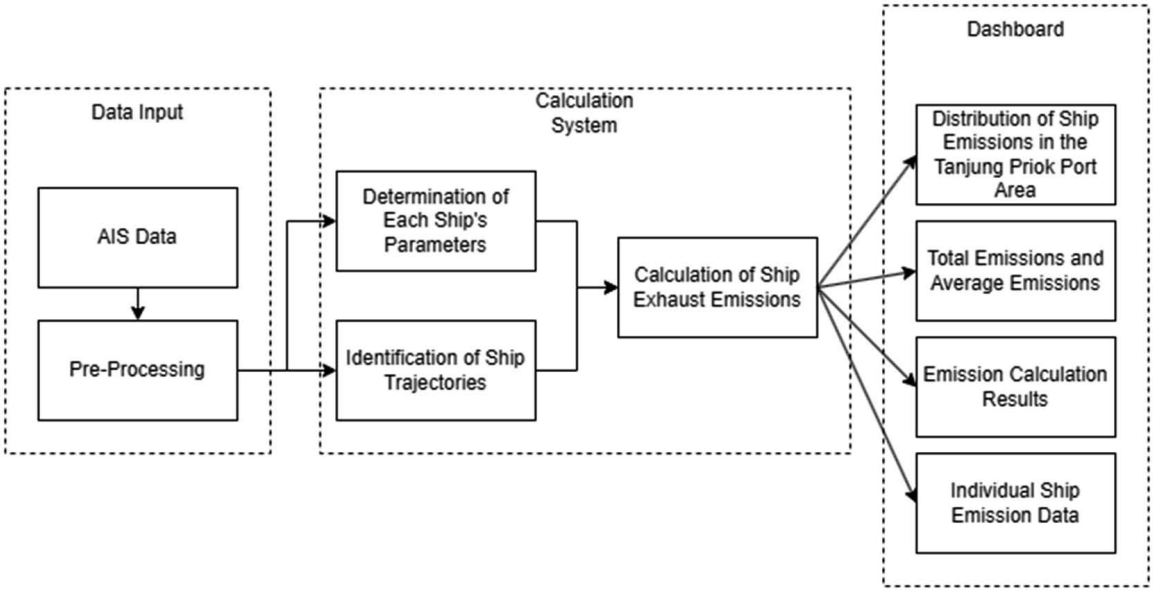


Figure 3 Research Flow Chart

lection of AIS data and a comprehensive literature review. Collected AIS data, which includes static and dynamic information about ships, undergoes preprocessing to ensure data quality and consistency. Static AIS data involves basic information about ships, such as Maritime Mobile Service Identity (MMSI), type, and dimensions. Meanwhile, dynamic AIS data includes real-time movement and activity information, such as coordinates, speed, and timestamps. This data is crucial for tracking ships and accurately assessing their emissions. Then, 15 AIS data samples are taken through the preprocessing process.

The next step is to determine parameters for each ship based on static AIS data. This involves updating AIS data according to MMSI to ensure accurate and up-to-date information. Regression analysis is then performed to estimate the power of the main and auxiliary engines as well as the design speed of the ship. These estimates are crucial for calculating ship emissions. Dynamic AIS data is used to identify ship trajectories. Each segment of the ship's journey is analyzed to calculate emissions using the STEAM model. This involves calculating sailing time and speed before estimating emissions for each segment and updating the ship emission database.

Finally, the processed data is visualized on an interactive web dashboard developed using Python, with front-end components built with HTML, CSS, and JavaScript. This dashboard provides monitoring and statistical visualization capabilities, enabling port authorities and stakeholders to make informed decisions to reduce the environmental impact of ship emissions. The entire system integrates data collection, processing, and visualization to provide a comprehensive tool for monitoring ship emissions at ports.

2.8.1 Preprocessing

Preprocessing AIS entails detecting, rectifying, or eliminating errors, inconsistencies, and anomalies within the dataset to guarantee that the data used for analysis or modeling is both reliable and accurate. This procedure, as illustrated in Figure 4, begins by loading raw data from CSV files using pandas, which is then organized into a structured format to allow for efficient manipulation and analysis. Key columns such as MMSI, name, IMO number, length, width, vessel type, latitude, longitude, and date time are retained, while unnecessary columns are removed to simplify the dataset. Duplicate entries are eliminated to maintain data integrity, and invalid coordinates are filtered to ensure spatial accuracy. Timestamp corrections and interpolations fill gaps for temporal reliability, while rows with invalid MMSI numbers or unrealistic ship dimensions are discarded. The cleaned data is then stored in a database for further use.

The database, designed to store AIS data for ship emission calculations, is implemented in MySQL. This database serves as a central repository that organizes AIS data, emissions, and other relevant data. The database structure, including tables, columns, data types, and relationships, is planned and created in detail using SQL commands. Data is entered manually or through automation scripts, and the MySQL database is integrated with the Django web framework for interactive data analysis and visualization. This process ensures a reliable and accurate dataset ready for the monitoring system.

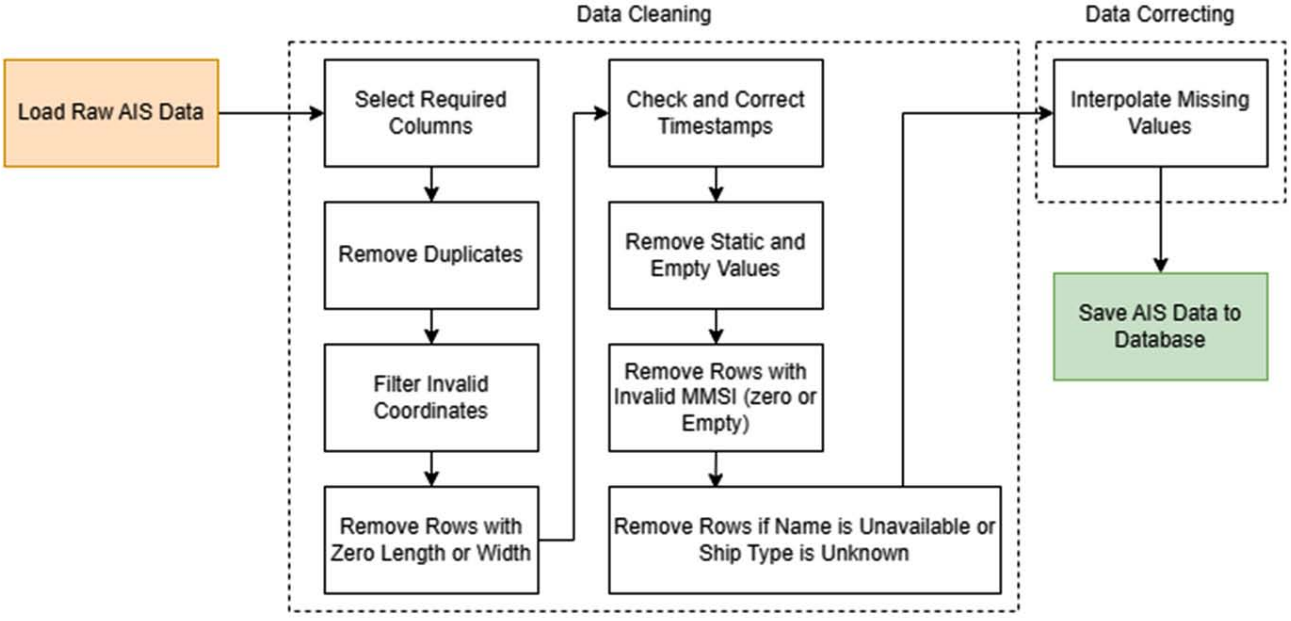


Figure 4 Preprocessing Flowchart

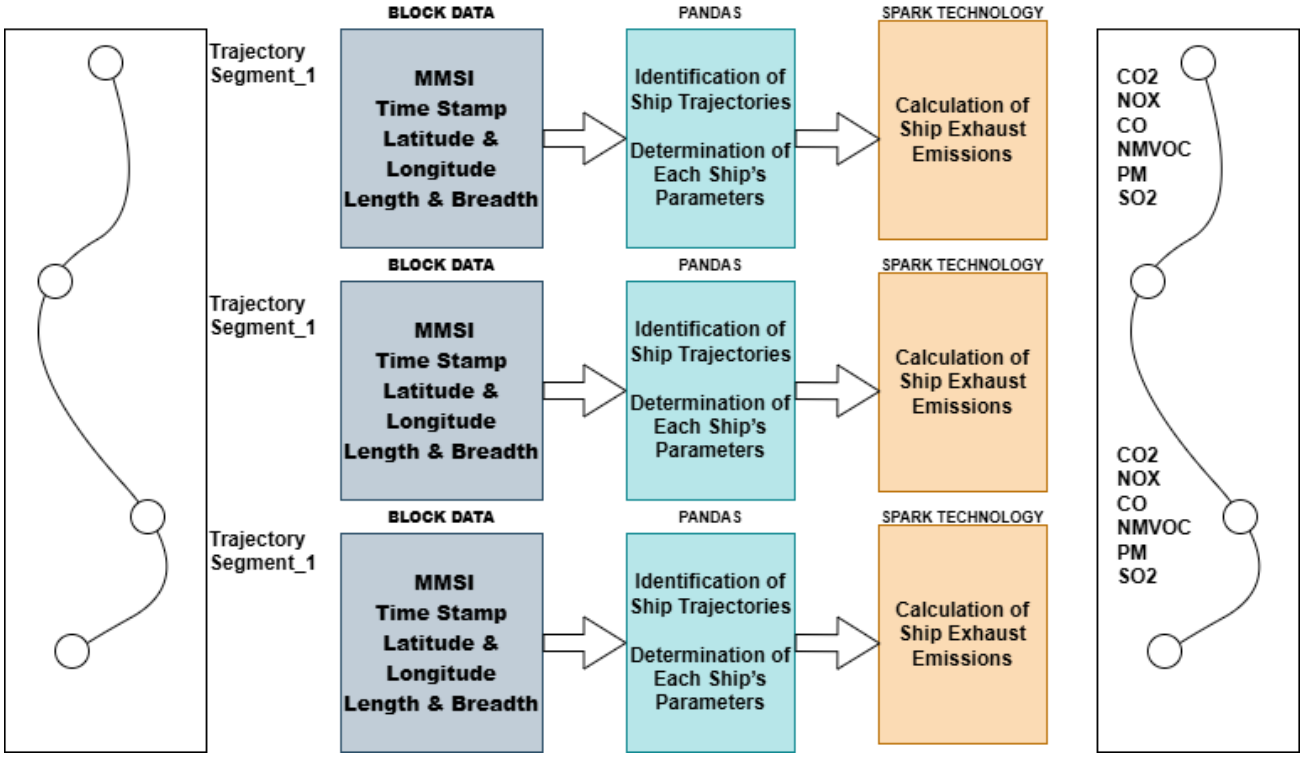


Figure 5 Distributed Emission Calculation Flow

2.8.2 Distributed Emission Calculation

Figure 5 illustrates the procedural framework for distributed emission calculations involves systematically assigning and processing computational tasks. The process begins, and data blocks are used to determine ship trajectories using Pandas. After trajectory segments are identified, ship parameters are calculated from these segments, using Pandas. Each segment of a ship's trajectory is subdivided into multiple data blocks, with each block serving as a fundamental unit for dynamic emission calculations. Once the data blocks are prepared, the Spark Engine allocates specific computational tasks to each block. These tasks utilize an advanced version of the STEAM model to estimate exhaust emissions for the corresponding trajectory segments. The tasks are executed in a First In, First Out (FIFO) sequence, ensuring systematic processing. Upon completion, the Spark Engine integrates the calculated emission results, which are promptly recorded in the database for further use.

After determining the selected MMSI for system development, AIS data is then sorted to produce data blocks that form trajectories for each ship. The calculation tasks are then assigned to calculate static and dynamic AIS data in a distributed manner. In this study, the author utilizes Pandas and Apache Spark to implement dynamic computational calculations. The calculations are carried out in sequence and efficiently process data blocks in batches within designated time intervals.

In the calculation process, key data elements such as emission factors and engine power ratios are critical for accurately estimating ship emissions using the STEAM model. Retrieving and processing this data manually would be highly time-consuming. To address this challenge, a big data storage solution, such as a MySQL database, is implemented to supply the essential information required for calculations efficiently. Prior to initiating the calculation process, this database ensures streamlined access to the necessary data, and these parameters will be arranged and stored in the database and connected to the calculations with the MySQL Connector so that the calculation program can easily access the required information.

The emission calculation process uses an enhanced version of the STEAM model proposed by [14] to estimate exhaust emissions from each ship. Equation 9 presents the formula for calculating ship exhaust emissions during sailing and mooring.

$$\begin{cases} E_i = P_m \times \left(\frac{\bar{V}_{ass}}{\bar{V}_{max}}\right)^3 \times T_m \times EF_{i,m} + P_a \times LF_a \times T_a \times EF_{i,a}, & \text{sailing} \\ E_i = P_a \times LF_a \times T_a \times EF_{i,a} + P_b \times T_b \times EF_{i,b}, & \text{mooring} \end{cases} \quad (9)$$

The subscript *i* indicates the specific type of pollutant, such as SO_x. The subscripts m, a, and b correspond to the main engine, auxiliary engine, and ship boiler, respectively. The variable E represents the quantity of pollutant emissions, while P indicates the engine power.

Additionally, the variables P and T denote the power output and operational duration of the ship's engine. The parameters EF and LF signify the emission factor and load factor of the engine, respectively. Furthermore, V_{max} represents the design speed or maximum service speed, and V_{oss} indicates the ship's actual operating speed.

3 Results

3.1 PreprocessingMA

The main data used for this research is the Big Data Automatic Identification System (AIS) provided by the Indonesian Maritime Security Agency (BAKAMLA RI). The collected AIS data focuses on the research object at Tanjung Priok Port.

Table 7 presents the specifications of AIS data received by the author, which include attributes such as MMSI, name, IMO, length, width, class, ship type, flag, COG, speed, latitude, longitude, destination, date time, heading, route, beam, draught, ETA, ship status, source, and flag.

The display of the ship trajectory validation program can be seen in Figure 6.

Figure 6 showing vessel movement and tracking accuracy in the Tanjung Priok Port area.

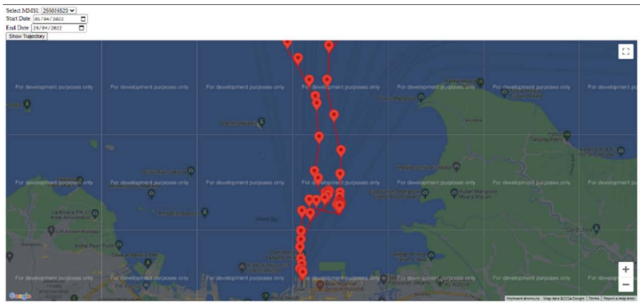


Figure 6 Displays of Ship Trajectory Validation Program

Based on this visualization, 15 ships from the obtained AIS data were identified using MMSI, as shown in Table 8.

Table 8 presents a list of tankers along with their key vessel attributes, including MMSI, name, IMO number, length, width, and vessel type. The data provides essential information for identifying and classifying tankers based on their dimensions and registration details. This dataset is useful for analyzing vessel characteristics, traffic patterns, and operational parameters within maritime logistics and port management.

Therefore, the sample AIS data records used total 16,432 records, as shown in Table 9.

Table 7 AIS Data RAW Specifications

Number of AIS Records	Number of MMSI	Number of Ship Types	First Timestamp	Last Timestamp
1.048.576	1.031	25	08/03/2022 17.00	09/06/2022 15.25

Table 8 Data on 15 Sample Ships

MMSI	Name	IMO	Length (Meter)	Width (Meter)	Vessel Type
255806523	APOLLO	9234628	26	167	Tanker
256520000	NEW RANGER	9328326	20	127	Tanker
351169000	ORALIA	9269609	18	118	Tanker
354996000	DIONNE	9814909	20	124	Tanker
355332000	DHEPOCH	9753648	22	120	Tanker
370229000	VALENTINE	9504023	21	134	Tanker
374548000	ASTREANA	9763629	14	97	Tanker
441530000	CT CONFIDENCE	9340427	24	145	Tanker
525003041	MT. ELISABET	9595668	10	75	Tanker
525003175	MT.KAKAP	9504401	18	108	Tanker
525003489	MT.LAPETTA	9004645	8	59	Tanker
525004010	PALU SIPAT	9106651	27	160	Tanker
525004138	TRANSKO AQUILA	9216042	14	93	Tanker
525007033	GAS MALUKU	9143154	20	100	Tanker
525007196	MT.FIGAR JAYA I	9636230	57	9	Tanker

Table 9 AIS Data Note Sample Data (First five rows)

MMSI	Name	IMO	Width (meter)	Length (meter)	Vessel Type	Latitude	Longitude	Date Time
255806523	APOLLO	9234628	26	167	Tanker	-6.03596	106.9188	17/04/2022 06:37
255806523	APOLLO	9234628	26	167	Tanker	-6.03576	106.9181	17/04/2022 03:19
255806523	APOLLO	9234628	26	167	Tanker	-6.03714	106.9193	16/04/2022 22:10
255806523	APOLLO	9234628	26	167	Tanker	-6.03613	106.919	17/04/2022 07:16
...	...	...	...	...	...	...	...	...

3.2 AIS Static Data Calculation Results

The calculation of AIS static data includes parameters such as main engine power, auxiliary engine power, and design speed data, which are computed using Python. To calculate the design speed, the ship's DWT data is required. The obtained DWT data is then entered into the database along with other supporting data. Table 10 shows the DWT data obtained according to the ships in the AIS sample data stored in the database.

The ship's DWT data is used to estimate the design speed, while the main and auxiliary engine power estimates use the ship's length and width data from the AIS records. The estimation results are presented in Table 11 and are then stored in the MySQL database.

Table 10 Ship DWT data

MMSI	IMO	Name	Vessel Type	DWT (Tonnes)
255806523	9234628	APOLLO	Tanker	23998
256520000	9328326	NEW RANGER	Tanker	12950
351169000	9259609	ORALIA	Tanker	8715
354996000	9814909	DIONNE	Tanker	12384
355332000	9753648	DH EPOCH	Tanker	13204
370229000	9504023	VALENTINE	Tanker	14214
374548000	9763629	ASTREANA	Tanker	3654
441530000	9340427	CT CONFIDENCE	Tanker	19993
525003041	9595668	MT. ELISABET	Tanker	3255
525003175	9504401	MT. KAKAP	Tanker	6523
525003489	9004645	MT. LAPETTA	Tanker	730
525004010	9106651	PALU SIPAT	Tanker	17957
525004138	9216042	TRANSKO AQUILA	Tanker	3592
525007033	9143154	GAS MALUKU	Tanker	5761
525007196	9636230	MT. FIGAR JAYA I	Tanker	1199

Table 11 Estimation Results of Design Speed, Main Engine Power, and Auxiliary Ship

MMSI	Vessel_type	Main Engine Power (kW)	Auxiliary Engine Power (kW)	Speed_Design (Knots)
255806523	Tanker	7488.724	1580.121	23.39
256520000	Tanker	2884.931	608.720	8.84
351169000	Tanker	2128.457	449.104	7.91
354996000	Tanker	2768.733	584.203	8.63
355332000	Tanker	3083.907	650.704	9.69
370229000	Tanker	3445.954	727.096	10.83
374548000	Tanker	1036.122	218.622	5.69
441530000	Tanker	5017.453	1058.683	14.40
525003041	Tanker	446.450	94.201	1.57
525003175	Tanker	1836.753	387.555	8.27
525003489	Tanker	258.604	54.566	2.64
525004010	Tanker	7419.517	1565.518	30.78
525004138	Tanker	971.548	204.997	5.20
525007033	Tanker	1925.200	406.217	10.13
525007196	Tanker	299.811	63.260	2.19

3.3 AIS Dynamic Data Calculation Results

Sailing speed is calculated by dividing the distance travelled between sequential AIS data points by the time difference. This calculation is essential for categorizing ship activities and understanding their operational modes. Table 12 shows the results of the sailing speed calculations.

Sailing time is calculated by determining the time difference between sequential AIS data points for each ship. The total sailing time is calculated by summing these differences, providing a comprehensive measure of the ship's activity duration.

The results of the sailing time calculations are shown in Table 13.

Table 12 Total Ship Sailing Time (First Three Rows)

MMSI	Speed (knots)	Date Time
255806523	10.84703643	16/04/2022 05:50
255806523	10.06962199	16/04/2022 06:01
255806523	10.89496867	16/04/2022 06:14
...	...	...

Table 13 Ship Sailing Speed (first three lines)

MMSI	Duration	Start Timestamp	End Timestamp
255806523	0.18	16/04/2022 05:50	16/04/2022 06:01
255806523	0.22	16/04/2022 06:01	16/04/2022 06:14
255806523	0.20	16/04/2022 06:14	16/04/2022 06:26
...	...	...	...

3.4 Ship Emission Calculation Results

Once all the necessary variables are complete, the ship emission calculation process can be carried out. In this experiment, the time period from April 1, 2022, to April 20, 2022, was used as shown in Table 14. The data required for the calculations is taken directly from the MySQL database.

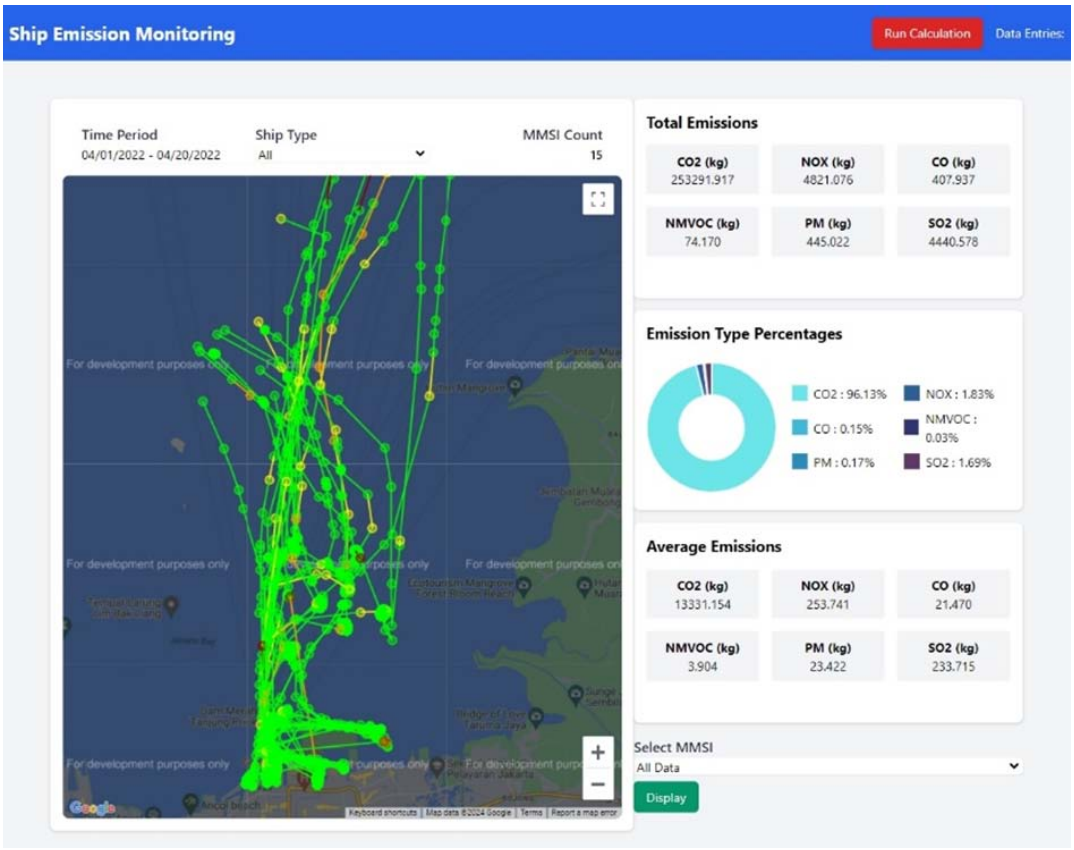
Table 14 presents the analysis of ship emission data collected over a 20-day period from April 1, 2022, to April 20, 2022, for 15 ships revealed significant variability in various emission parameters, providing insight of the ecological effects of maritime activities. The emission data analysis revealed important insights into the distribution and characteristics of various pollutants. It is important to note that data showing a value of 0 reflects situations where the calculated data duration is 0, resulting in the emission calculation being 0 as well. This can occur when ships are docked in port or undergoing loading and unloading processes.

This dataset consists of total recorded emissions dominated by CO_2, accounting for 96.12% of total emissions, amounting to (253,291.927 kg). This is followed by NOx at 1.83% (4,821.076 kg), SO_2 at 1.69% (4,440.578 kg), PM at 0.17% (445.022 kg), CO at 0.15% (407.937 kg), and NMVOC at 0.03% (74.170 kg). The percentage of these emission types highlights the dominance of CO_2 in contributing to total emissions. In terms of average emissions per pollutant type recorded, CO_2 again leads with an average emission of 13,331.154 kg. NOx follows with an average of 253.741 kg, SO_2 with 233.715 kg, PM with 23.422 kg, CO with 21.470 kg, and NMVOC with 3.904 kg.

Table 14 Deduction of ship emissions calculation results (with time period 04/01/2022 – 04/20/2022)

MMSI	CO_2 (Kg)	NO_x (Kg)	CO (Kg)	NMVOC (Kg)	PM (Kg)	SO_2 (Kg)
255806523	955.743	18.191	1.539	0.280	1.679	16.113
255806523	1129.514	21.499	1.819	0.331	1.985	19.043
...	...	...	...	...	...	...
256520000	334.716	6.371	0.539	0.098	0.588	5.643
256520000	267.773	5.097	0.431	0.078	0.470	4.515
...	...	...	...	...	...	...
351169000	296.338	5.640	0.477	0.087	0.521	4.996
351169000	98.779	1.880	0.159	0.029	0.174	1.665
...	...	...	...	...	...	...
354996000	674.592	12.840	1.086	0.198	1.185	11.373
354996000	14385.481	7.337	0.621	0.113	0.677	6.499
...	...	...	...	...	...	...
355332000	429.361	8.172	0.692	0.126	0.754	7.239
355332000	26.734	0.509	0.043	0.008	0.047	0.481
...	...	...	...	...	...	...
370229000	239.884	4.566	0.386	0.070	0.421	4.044
370229000	159.923	3.044	0.258	0.047	0.281	2.696
...	...	...	...	...	...	...
374548000	120.213	2.288	0.194	0.035	0.211	2.027
374548000	12.021	0.229	0.019	0.004	0.021	0.203
...	...	...	...	...	...	...
441530000	349.281	6.648	0.563	0.102	0.614	5.889
441530000	174.641	3.324	0.281	0.051	0.307	2.944
...	...	...	...	...	...	...
525003041	4.838	0.092	0.008	0.001	0.008	0.087
525003041	4.838	0.092	0.008	0.001	0.008	0.087
...	...	...	...	...	...	...
525003175	277.035	5.273	0.446	0.081	0.487	4.671
525003175	213.104	4.056	0.343	0.062	0.374	3.593
...	...	...	...	...	...	...
525003489	2.242	0.043	0.004	0.001	0.004	0.040
525003489	2.242	0.043	0.004	0.001	0.004	0.040
...	...	...	...	...	...	...
525004010	1205.159	22.939	1.941	0.353	2.117	20.318
525004010	258.248	4.915	0.416	0.076	0.454	4.354
...	...	...	...	...	...	...
525004138	8.422	0.160	0.014	0.002	0.015	0.152
525004138	8.422	0.160	0.014	0.002	0.015	0.152
...	...	...	...	...	...	...
525007033	178.693	3.401	0.288	0.052	0.314	3.013
525007033	178.693	3.401	0.288	0.052	0.314	3.013
...	...	...	...	...	...	...
525007196	34.785	0.662	0.056	0.010	0.061	0.586
525007196	34.785	0.662	0.056	0.010	0.061	0.586
...	...	...	...	...	...	...

3.5 Monitoring Dashboard



Emission Data

MMSI	Start Timestamp	End Timestamp	Vessel Type	CO2 (kg)	NOX (kg)	CO (kg)	NMVOC (kg)
525003489	2022-04-01 00:00:00	2022-04-01 00:12:00	Tanker	2.241781518779489	0.04266934076739876	0.0036104826803183576	0.0006564513964215 19
525004138	2022-04-01 00:04:00	2022-04-01 00:16:00	Tanker	8.422125395084716	0.1603039972710122	0.013564184384470263	0.002466215342630956
525003041	2022-04-01 00:11:00	2022-04-01 00:26:00	Tanker	4.837716375468139	0.09207952105576252	0.007791344089333752	0.001416608016242500
	2022-04-01	2022-04-01					

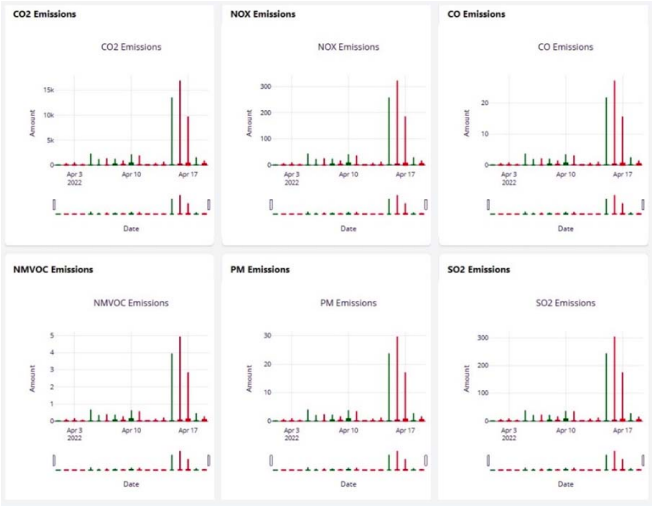


Figure 7 Monitoring Dashboard User Interface

The user interface (UI) is designed to be intuitive and user-friendly to facilitate access and interpretation of complex emission data, as shown in Figure 7. User feedback indicates that the interface effectively conveys data, with users appreciating the interactive map and real-time data updates. The ability to visualize emissions spatially and temporally provides stakeholders with a clear understanding of emission patterns and their implications. Front-end development plays a crucial role in enhancing the accessibility and usability of the emission monitoring system, supporting informed decision-making and policy development.

The back-end system also performs well, efficiently handling multiple data requests and ensuring timely updates to the front-end. This design is intended to scale with increasing data volumes to ensure that the system can accommodate future AIS data and emission calculations. The integration of Django with the MySQL database enables seamless data interaction and processing, meeting the requirements of the ship emission monitoring system. The back-end development provides a solid foundation for the overall system's functionality and performance, ensuring that data is processed and delivered accurately and efficiently.

4 Discussion

The proposed big data-based framework for a ship emission monitoring system is adaptable for implementation in other ports where high maritime traffic significantly contributes to air pollution. As long as ships within a port area are required to transmit AIS data, this data can be processed and utilized as a source for emission monitoring. Expanding this system would enable real-time emission tracking, allowing port authorities to develop localized control strategies and ensure compliance with IMO's MARPOL Annex VI [31] and national regulations. Integrating this system across multiple ports would facilitate data-sharing and coordinated policy-making, enhancing the port's efforts to reduce greenhouse gas emissions in maritime operations. Although the system has been tested using historical AIS data, it has not yet been validated against real-world emission measurement data. This validation process is identified as a key objective for future system development. Successful implementation requires digital infrastructure readiness, operational adaptability, and regulatory alignment, ensuring a seamless transition to a unified national ship emission monitoring network.

5 Conclusions

This research aims to develop a web-based ship emission monitoring system that utilizes AIS data and various related calculations to provide comprehensive information on ship pollutant emissions through a system supported by a structured MySQL database that stores emission and other operational ship data. The system is integrated with the Django framework to retrieve, process, and display data through an interactive and user-friendly web interface that can be used by decision-makers, primarily at Tanjung Priok Port, in efforts to control ship emissions in the port area.

To enhance system automation, future work will involve validating the estimated emissions against actual onboard emission measurements to improve the system's accuracy and reliability. Implementing a DWT estimation method or alternatively providing access to classification society data or port data would be beneficial. Developing faster calculation methods is also necessary to process larger datasets. Furthermore, developing more detailed calculation methods tailored to the Tanjung Priok Port area is needed

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