Wang, J, Li, H, Yang, Z and Ge, YE

A novel scheme for shore power data to enhance containership-at-berth emission estimation

Transportation Research Part D 134 (2024) 104353

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

A novel scheme for shore power data to enhance containership-at-berth emission estimation

Jinggai Wang [a,b], Huanhuan Li [b,*], Zaili Yang [b,*], Ying-En Ge [c]

[a] College of Transport and Communications, Shanghai Maritime University, Shanghai, China
[b] Liverpool Logistics, Offshore and Marine (LOOM) Research Institute, Liverpool John Moores University, Liverpool, UK
[c] School of Transportation Engineering, Chang'an University, Xi'an, Shannxi, China

ARTICLE INFO

Keywords:
Shore power
Ship-at-berth emissions
Comparative analysis
Influence factor
Emission reduction measures

ABSTRACT

Ship-at-berth emissions significantly affect air quality and health of human beings in a port and its neighbourhood. However, it is challenging to estimate these emissions precisely due to stringent data requirements. Shore Power (SP) data, including its actual energy consumption and duration, offers useful insights to refine these estimates, but has yet to be fully explored. This study proposes a novel scheme incorporating SP data to improve the accuracy of containership-at-berth emission estimates and evaluate emission reduction measures. The findings reveal substantial differences among existing emission estimates from identical case studies, highlighting the importance of SP data. Additionally, it demonstrates significant emissions from low-load main engines and confirms the efficacy of SP in emission reduction. These findings provide valuable insights into emission estimation methods and their potential applications in estimating emission reduction measures, underlining the importance of policy support in facilitating the SP implementation.

1. Introduction

Maritime transport is crucial to international trade and the global economy, handling more than 80% of global trade by volume and about 70% by value (United Nations, 2018). International shipping, despite being one of the most eco-friendly transportation modes, contributed around 10% of the transportation industry's total emissions in 2022 and roughly 2.1% of global Carbon Dioxide (CO_2) emissions, as illustrated in Fig. 1 (Singh et al., 2023). Additionally, the shipping industry is a major source of Sulphur Dioxide (SO_2), Particulate Matters (PM), Nitrogen Oxides (NO_X), and other air pollutants, posing further environmental and health risks. It is worth noting that ship emissions can travel across borders and impact marine environment and air quality in the surrounding areas of ports (Poulsen et al., 2018). Hence, it is a significant challenge to address these emissions, even with increased research efforts over the past decade.

Given the substantial costs involved in equipping ships with emission monitoring equipment on ships (Lee et al., 2020), the estimation of ship emissions often relies on data concerning fuel sales, fuel consumption, and ship characteristics. The studies on ship emissions are characterised by the following: 1) A significant portion of recent research has been dedicated to evaluating emissions on various scales, including global, regional, port, and voyages. For instance, Corbett and Fischbeck (1997) analyse global fleet emissions

* Corresponding authors.
E-mail addresses: wangjinggai01@stu.shmtu.edu.cn (J. Wang), H.Li2@ljmu.ac.uk (H. Li), z.yang@ljmu.ac.uk (Z. Yang), yege@chd.edu.cn (Y.-E. Ge).

https://doi.org/10.1016/j.trd.2024.104353
Received 28 May 2024; Received in revised form 17 July 2024; Accepted 31 July 2024
Available online 8 August 2024

Abbreviations

ABs	Auxiliary Boilers
AIS	Automatic Identification System
AEs	Auxiliary Engines
CO_2	Carbon Dioxide
CO	Carbon monoxide
DWT	Deadweight Tonnage
ECAs	Emission Control Areas
EU	European Union
GRT	Gross Register Tonnage
GT	Gross Tonnage
HFO	Heavy Fuel Oil
IMO	International Maritime Organization
LA series report on emission inventory	Series Reports on emission inventory for the Port of Los Angeles
LSHFO	Low Sulphur Heavy Fuel Oil
MEs	Main Engines
MDO	Marine Diesel Oil
MGO	Marine Gas Oil
MCR	Maximum Continuous Rating
NT	Net Tonnage
NO_X	Nitrogen Oxides
PM	Particulate Matters
RPM	Revolutions Per Minute
$SFOC$	Special Fuel Oil Consumption
SO_X	Sulphur Oxides
SP	Shore Power
TEU	Twenty-foot Equivalent Unit

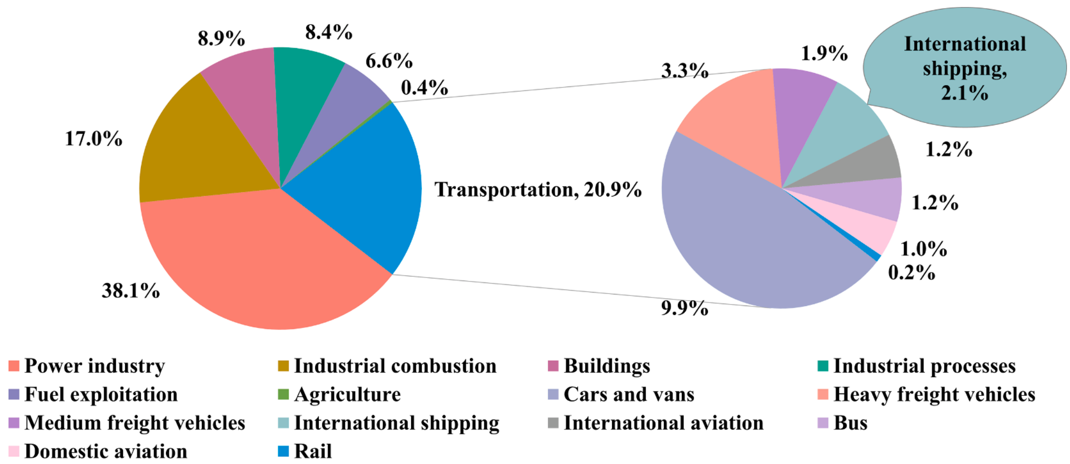


Fig. 1. The distribution of global CO_2 emissions by sector in 2022 (Source: EC & IEA).

by ship type, while Starcrest (2023) estimates ocean-going vessel emissions in the port areas. 2) The main methods of estimating ship emissions in different phases, classified as top-down and bottom-up approaches, are relatively straightforward (Peng et al., 2024a). 3) With stricter regulations on pollution than before, there has been a surge in research concentrated on the application of these methods to evaluate the emission reduction measures, including slow steaming, Emission Control Areas (ECAs), the 2020 global sulphur limit, renewable energy source, and all-electric ships (Wang et al., 2023b).

As indicated by He et al. (2023), most ships' emissions in ports occur at berth, making it a critical and efficient strategy for maximally mitigating vessel emissions in ports. However, ship-at-berth emissions have hindered progress in this area due to data limitations, a complex berthing process, and a misconception that these emissions are minimal compared to total voyage emissions. Shore Power (SP), a system enabling ships to switch off their Auxiliary Engines (AEs) and connect to onshore power grids while docked,

Table 1
Categories, advantages, disadvantages, applicability, and references of different emission methods.

Categories	Methods	Advantages	Disadvantages	Applicability	Refs.
Ship emissions estimation	Top-down: fuel-based method	Does not require detailed ship navigation data; popular in the late 1990s and early 2000s.	Heavily depend on the precision of fuel sales data; significant inaccuracies can lead to considerable uncertainty.	Best suited for broad, global ship emission estimations and provides only approximate figures.	Corbett and Fischbeck (1997)
	Top-down: trade-based method	Useful for estimating ship-in-port emissions; and focus on cargo or passenger throughput at ports.	Has a large margin of error compared to the fuel-based method; less extensively used for overall ship emissions estimation.	More applicable to port-specific emissions calculations.	Liu et al. (2018), Li and He (2011)
	Bottom-up: statistical method	Offer enhanced precision and spatiotemporal resolution by focusing on ship activities and characteristics.	Depend on the availability of empirical data.	More applicable to ship emissions calculations in different phases.	Wang et al. (2024), Corbett and Koehler (2003)
	Bottom-up: dynamic method	Offer precise references crucial for ship design and the formulation of emission policies.	Require utmost precision in data related to different operational modes, comprehensive details on ship features, navigation, and weather conditions, and advanced data processing capabilities.	Ideal for detailed, specific emission studies, requiring high accuracy and resolution, especially where comprehensive ship data is accessible.	Shu et al. (2023), Peng et al. (2024b)
Ship-at-berth emissions estimation	Methods without specific engine type consideration	It is accessible and easy to implement, due to the reduction of complexity in data collection and processing.	Oversimplify the complex relationship between engines and emissions, leading to estimates that could misinform operational decisions.	Used for a rough estimation of emissions at various stages, studying the emission trends of ships.	(Hickman et al., 1999), Trozzi and Vaccaro (2006)
	Methods specifically concentrating on AEs	Offer a more detailed and straightforward analysis, and simplify the process.	Neglect emissions from ABs and low-load MEs during berth activities, resulting in an incomplete assessment.	Suited for studies that focus specifically on the impact of AEs on air quality, including analyses related to SP.	Nguyen et al. (2022), Shu et al. (2023)
	Methods take into account both AEs and ABs	Provide a more holistic view of emissions during specific periods.	Overlook emissions from low-load conditions of MEs, leading to an underestimation of emissions.	Widely used for assessing emissions during ship berthing.	Chen et al. (2021), Starcrest (2023)

is emerging as an effective means to reduce ship-at-berth emissions (Wang et al., 2023a). The growing adoption of SP and the associated energy consumption and duration data offer an alternative for estimating ship-at-berth emissions from AEs. This paper incorporates real SP energy consumption and duration data (SP data) instead of the estimation of AEs to improve estimations of ship-at-berth emission from AEs and then explore to enhance estimations of ship-at-berth emissions from all possible operational engines to bridge these research domains. It, thereby, enables a more effective assessment of 10 kinds of classical emission reduction measures (i.e., Marine Gas Oil (MGO), Low Sulphur Heavy Fuel Oil (LSHFO), ECA, Outside-ECA, HFO and Scrubber, HFO and SP, MGO and SP, LSHFO and SP, ECAs and SP, and Outside-ECA and SP) for types of five pollutants (i.e., CO_2, CO, NO_X, SO_2, and PM). It is imperative to note that emissions from SP and AEs are excluded from the estimation when SP is utilised. The intellectual merits of this paper are highlighted as follows:

(1) A thorough review of influential factors and their corresponding parameters allows for the advancement of existing at-berth estimation methods, identifying research gaps in the process.

(2) SP data is employed to improve the methods of estimating ship-at-berth emissions from AEs, thereby replacing traditional estimation techniques.

(3) A practical approach to estimating ship-at-berth emissions is introduced, taking into account AEs, Auxiliary Boilers (ABs), and low-load Main Engines (MEs).

(4) Analysis of the effectiveness and accuracy of the proposed emission estimation method is carried out, including an assessment of the roles that emissions from ABs and MEs play.

(5) Integration of existing ship-related emission reduction measures into the proposed method is to draw useful insights and suggestions for promoting and managing SP.

The structure of the paper is organised as follows: Section 2 provides an in-depth literature review of the state-of-the-art methods of estimating ship-at-berth emissions, influential factors, and associated parameters and reveals research gaps. Section 3 outlines an enhanced methodology for estimating ship-at-berth emissions from AEs using SP data and introduces a novel and practical scheme for ship-at-berth emission estimation from all possible operational engines. Section 4 encompasses case studies and analysis to demonstrate the performance of the improved AEs' estimation with SP data, proposed method, and its applications in various reduction measures. Finally, Section 5 offers concluding remarks and a discussion on associated policy implications and limitations.

2. Literature review

Ship-at-berth emissions are influenced by multiple factors, including types and conditions of the engines, fuel type, ship's characteristics, berth time, regulations and compliance, and emission reduction measures. Each factor has its own set of specific parameters, and it is common for a detail to be affected by several factors. To elucidate this relationship clearly, this paper structures the review into three subsections: 1) the current state-of-the-art methods of estimating ship emissions; 2) an exploration of factors and their associated parameters; and 3) research gaps are identified at the end.

2.1. Research progress of ship-at-berth emissions

Ship emissions estimation is critical for understanding and mitigating the environmental impact of maritime activities. As summarised by Wang et al. (2024), this study outlines the categories, advantages, disadvantages, and applicability of various emission estimation methods in Table 1, providing a comparative overview to aid in selecting the most appropriate method for specific emission estimation needs. Specifically, the fuel-based method depends on the strong correlation between fuel consumption and emissions, integrating data on marine fuel sales with information on ship types, voyage areas, and engine distribution to allocate total emissions. The trade-based method estimates ship emissions based on cargo throughput at ports by fitting functions. Despite its utility, the top-down method is less commonly employed in ship emissions studies for its broader and more generalised estimate of emissions. Conversely, the bottom-up method offers a more granular view by focusing on the actual activities of ships. It incorporates detailed data on ship characteristics, technical information, and movements to estimate emissions more precisely.

Although representing a smaller portion of total ship emissions, the existing methods of estimating ship-at-berth emissions are similar to, yet differ from, those of overall ship emissions. This paper divides the estimation methods into distinct classifications based on their approaches against engine type considerations: methods that do not differentiate by engine type, those that focus solely on AEs, and those that take into account both AEs and ABs. Regarding methods that do not specify engine type, emissions are calculated based on the number of sailing days, providing a broad estimate that is easier to apply but may not capture the detailed variations in different engine activities (Hickman et al., 1999; Trozzi and Vaccaro, 2006). Methods specifically targeting AEs focus on emissions from AEs during ship berthing, which is widely used in the maritime sector today to estimate ship-at-berth emissions. For instance, Nguyen et al. (2022) employ bottom-up methods to estimate these emissions at ten major container ports in Southeast Asia, considering only the operation of AEs. Methods that take into account both AEs and ABs have recently emerged, providing a more comprehensive assessment of ship-at-berth emissions. For example, Chen et al. (2021) utilise default engine loads and emission factors for both AEs and ABs to estimate ship-at-berth emissions as part of port emissions. These methods are documented in sources, including IMO series reports, Series Reports on emission inventory for the Port of Los Angeles (LA series reports on emission inventory) (Port of Los Angeles, 2024), and EPA (2020). They are commonly encountered in port emission assessments.

Table 2
Methods and classifications for determining the power of AEs, ABs, and MEs.

Engine type	Parameters	Methods of determining ME power	Classification	Refs.
AEs	P_{AE}	$P_{AE} = f(\textit{ship size})$.	Given ship type	Wang et al. (2007b) and Daniel et al. (2021)
		Default ratio of P_{ME} to P_{AE}	Default ratio with P_{ME}	Lee et al. (2021)
		$P_{AE} = GRT \times PRT$	Power-to-Tonnage Ratio	Adamo et al. (2014)
		$P_{AE} = f(DWT)$, $P_{AE} = f(GT)$, and$P_{AE} = f(TEU)$.	Multiple regression	Gligor et al. (2021), Dai et al. (2019), and Gutierrez-Romero et al. (2019)
		Empirical data.	Consideration of ship types and operational modes	EPA (2020)
	L_{AE}	Related to operational mode, types, and sizes of vessels, using default values.	Default value	Starcrest (2021)
		$L_{AE} = GRT \times PRT \times EL_{AE}$.	Regression	Adamo et al. (2014)
		$L_{AE} = P_{AE} \times EL_{AE}$.	Regression	Styhre et al. (2017)
ABs	L_{AB}	Overlooked.	N/a	Adamo et al. (2014)
		Integrated with L_{AE}.	Merged	Jalkanen et al. (2012)
		Default ratio of L_{AE} to L_{AB}.	Fitting function	Stolz et al. (2021)
		AIS data with EU monitoring, reporting, and verification data.	Calculated based on extensive data	Yang (2021)
		$L_{AB} = f(\textit{ship size})$.	Default value	Zis et al. (2014)
MEs	P_{ME}	Provided by shipyard.	Survey	Cooper and Gustafsson (2004b)
		$P_{ME} = f(\textit{length}, \textit{speed}, DWT)$.	Fitting function	IMO (2021)
		Collected from the sister vessels.	Default value	Tichavska et al. (2019)
		The average power of the same ship type.	Default value	Faber et al. (2020)
	MCR	$MCR = f(\textit{weight tonnage}, \textit{ship type})$.	Multiple regression	Lee et al. (2021)
		$MCR = 80\% \times P_{ME}$.	Default value	Jalkanen et al. (2009)
		Vessel database.	Database	Lloyd's Register of Shipping, China Classification Society, American Bureau of Shipping, etc.
	Instantaneous power	Related to frictional resistance, wave resistance, and turbine resistance.	Multiple regression	Jalkanen et al. (2009)
		Related to speed and resistance.	Multiple regression	IMO (2021)
		Related to MCR and L_{ME}.	Multiple regression	Styhre et al. (2017)

Note: Gross Register Tonnage (GRT) measures the total internal volume of a vessel, while the Power-to-Tonnage Ratio (PRT) represents the power required per unit of tonnage. P_{AE} can be estimated using the formula $P_{AE} = GRT \times PRT$.

2.2. Review of influential factors and associated parameters for ship-at-berth emissions

The assessment of ship-at-berth emissions is shaped by a variety of factors, leading to a range of diverse parameters. Among these, the types of ship engines, ranging from AEs, ABs, and MEs, play a crucial role in the overall estimations. AEs are especially significant as they power vital onboard systems such as refrigeration, air conditioning, lighting, and the operation of refrigerated containers loading, unloading, or when passengers are getting on or off the ships (Zis, 2019). Key parameters for AEs include its installed power (P_{AE}), Engine Load (EL_{AE}), and the actual operational power or Load (L_{AE}). ABs play a crucial role in maintaining stable temperatures for fuel and the ME's cylinders, preventing damage from low-temperature shrinkage (Zis, 2019). When a ship is berthed, ABs start operational, marking them as significant sources of ship-at-berth emissions. The primary parameter for ABs is their power, denoted as L_{AB}. MEs are the primary power source for ships, driving propulsions and being the main emission contributors while navigating. Key parameters for MEs' emissions include the installed ME Power (P_{ME}), Engine Load (EL_{ME}), Maximum Continuous Rating (MCR), and operational power or load (L_{ME}). While it is common to assume the MEs are turned off during docking, emerging research, including field studies and interviews, shows that MEs often operate at a low load (Kotrikla et al., 2017), significantly impacting emissions of pollutants like carbon monoxide (CO) and PM. This review divers into different methods of determining P_{AE}, L_{AE}, L_{AB}, and ME power as outlined in Table 2.

Special Fuel Oil Consumption ($SFOC$) is a key indicator of a ship's fuel efficiency, measuring fuel consumption relative to engine power in grams per kilowatt-hour (g/kWh). There is a quadratic relationship between $SFOC$ and EL, with the lowest $SFOC$ occurring when EL is between 70% and 80%, it can increase up to 1.7 times above the standard value at low loads (Jalkanen et al., 2012; Daniel

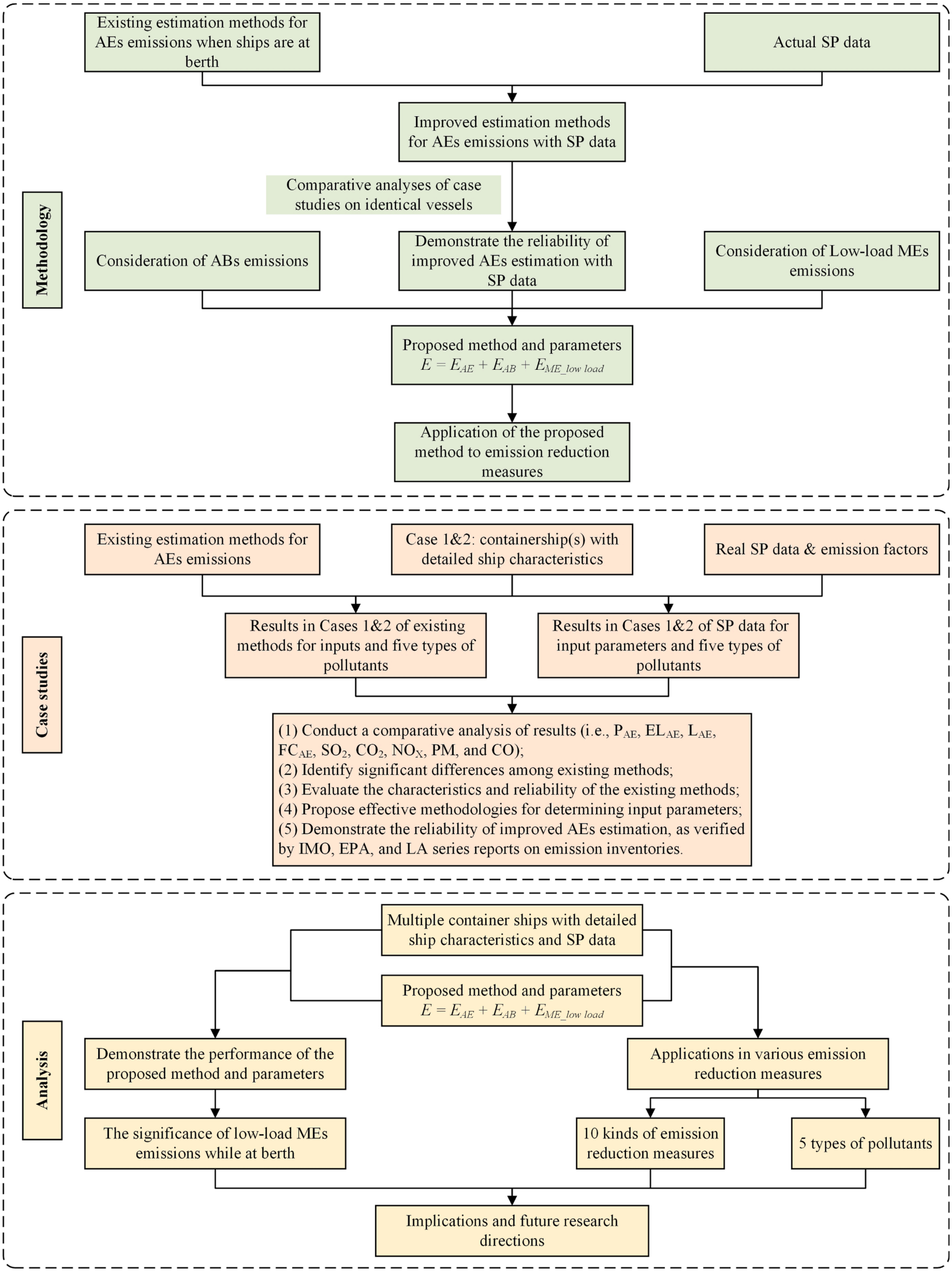


Fig. 2. The proposed framework.

et al., 2021). Furthermore, ships utilise a range of fuel types, including HFO with 2.7% sulphur content (2.7% HFO), LSHFO with 1% sulphur content (1% LSHFO), MGO or Marine Diesel Oil with 0.1% sulphur content (0.1% MGO or MDO), as well as alternative fuels like liquefied natural gas, methanol, hydrogen, ammonia, and even nuclear energy. The type of fuel chosen significantly affects fuel consumption and emission factors (Faber et al., 2020). It is notably challenging to obtain accurate emission factors due to the high costs and complex methodologies involved, as well as the need for detailed and high-quality experimental data. Consequently, current calculations often rely on data from earlier studies, such as those by the Swedish IVL Research Institute in 2004 and Entec in 2002 (Cooper and Gustafsson, 2004a; Cooper and Gustafsson, 2004b). Additionally, the varied characteristics of pollutants increase the complexity and uncertainty in estimating emission factors accurately (Starcrest, 2021).

2.3. Research gaps

Given the reviews of research progress and influential factors, this paper reveals the following research gaps:

(1) Current studies often view ship-at-berth emissions as merely part of overall ship emissions, overlooking the unique characteristics and complexities of the berthing phase.

(2) It is challenging to accurately estimate ship-at-berth emissions due to the need for data on detailed ship and activity, berthing duration, and fuel types.

(3) Operations at low-load MEs are often overlooked without reasonable explanations of their impact on the estimate accuracy.

(4) Variations in determining the parameters associated with ship-at-berth emissions often result in inconsistent and inaccurate results, lacking comparative analysis with the same cases.

As an important intermediate variable in calculating ship-at-berth emissions, SP data could provide an opportunity to investigate ship-at-berth emissions from a new perspective. This paper screens a series of classical and foundational references that employ distinct calculations and parameters to estimate ship-at-berth emissions. Based on the reviews by Wang et al. (2024) and Lee et al. (2021), there are two primary approaches within the bottom-up method: Fuel Consumption (FC) methods and Energy Output (EO) methods. FC methods estimate emissions by considering the total fuel consumed and applying fuel-based emission factors, while EO ones calculate emissions based on the energy output and energy-based emission factors. Emissions estimated by FC methods can sometimes be converted to EO methods using *SFOC*. To highlight the difference between them. This paper has categorised the 37 identified methods into two groups: FC and EO, labelled as FC-1, FC-2, EO-1, and EO-2. For detailed information, refer to Appendix Table A1. By comparing the differences between estimation results derived from these existing methods and real SP data within the investigated containerships, this study assesses the reliability of using SP data over traditional methods for estimating ship-at-berth emissions from AEs. Based on these comparisons and a thorough literature review, this paper proposes a novel scheme for using SP data to enhance emission estimation from all possible operational engines when ships at berth, effectively filling the existing research gaps.

3. Methodology

3.1. The research framework

Rooted in the advancements of SP promotion and application, the research framework of this paper contains three parts: methodology, case studies, and analysis, as displayed in Fig. 2.

Methodology: This paper first reviews 37 primary methods for estimating ship-at-berth emissions from AEs. Subsequently, it utilises actual SP data to enhance and refine these existing estimation methods for AE emissions. Through a comparative analysis of identical vessels, this paper evaluates the characteristics of existing methods and demonstrates the reliability of the improved AEs emission estimation method. Furthermore, leveraging the strengths of the improved method and insights from the literature review, a novel approach is proposed for estimating ship-at-berth emissions. This new method takes into account AEs, ABs, and low-load MEs, along with recommended fuel-related parameters, to estimate emissions from all possible operational engines on the ship while at berth. Finally, the proposed method is employed to evaluate key emission reduction measures within the maritime industry.

Case studies: this paper conducts case studies on both a single containership and multiple containerships of varying sizes to compare the results derived from the established methods for AEs and improved methods using SP data, including P_{AE}, EL_{AE}, L_{AE}, FC_{AE}, SO_2, CO_2, NO_X, PM, and CO. Through extensive statistical and comparative analyses, this paper identifies significant differences among existing methods. Additionally, it evaluates the characteristics and reliability of existing methods, proposes effective ways for determining input parameters, and confirms the reliability of improved AEs estimation, as verified by IMO, EPA, and LA series reports on emission inventories.

Analysis: Employing vessel characteristics, validated fuel-related parameters, SP data, and the proposed method, this paper assesses emissions from AEs, ABs, and low-load MEs for multiple containerships. Taking HFO as the benchmark fuel, the proposed method is applied to estimate the effectiveness of 10 classical emission reduction measures, including MGO, LSHFO, ECAs, Outside-ECAs, HFO and Scrubber, HFO and SP, MGO and SP, LSHFO and SP, ECAs and SP, and Outside-ECAs and SP, targeting five types of pollutants: CO_2, CO, NO_X, SO_2, and PM. Finally, the implications and future research directions for both practical and academic areas are outlined.

3.2. The proposed method

Upon investigation with senior crews, it has been noted that the load of MEs is not idle at a zero state in actual ship operations. Instead, it continues to operate under low-load conditions ($EL_{ME} < 20\%$) for a certain duration, approximately 5% of the total berthing

Table 3
List of notations used in this study.

Notations	Definitions
C and S	The concentrations of carbon and sulphur in fuel (%).
CVs	Coefficient of variation.
CV_{CO}, CV_{CO_2}, $CV_{FC_{AE}}$, $CV_{L_{AE}}$, CV_{NO_x}, CV_{PM}, and CV_{SO_2}	Coefficient of variation of CO, CO_2, FC_{AE}, L_{AE}, NO_x, PM, and SO_2.
E	Ship-at-berth emissions (g).
E_{AB}, E_{AE}, and $E_{ME\_lowload}$	Ship-at-berth emissions from ABs, AEs, and low-load MEs, respectively (g).
EO_{AB}, EO_{AE}, and $EO_{ME\_lowload}$	Energy out of ABs, AEs, and low-load MEs, respectively (kW).
EO_{SP_AE}	Real SP energy consumption (kWh).
EF	Emission factors.
EF_{AB}, EF_{AE}, and EF_{ME}	Emission factors for ABs, AEs, and MEs, respectively.
EF_{CO}, EF_{CO_2}, EF_{NO_x}, EF_{PM}, and EF_{SO_2}	Emission factor of CO, CO_2, NO_x, PM, and SO_2, respectively.
EF_e	Energy-based emission factor (g/kWh).
EF_{e_AB}, EF_{e_AE}, and EF_{e_ME}	Energy-based emission factors for ABs, AEs, and MEs, respectively (g/kWh).
EF_f	Fuel-based emission factor (g/g).
EL_{AE} and EL_{ME}	Engine load of AEs and MEs, respectively (%).
FC	Fuel consumption (g).
FC_{AB}, FC_{AE}, and FC_{ME}	Fuel consumption of ABs, AEs, and MEs, respectively (g).
L_{AB}, L_{AE} and L_{ME}	The load of ABs, AEs, and MEs, respectively (kW).
LLF	Low Load Emission Adjustment Factor, is used to adjust the emissions from MEs operating at low load.
LLF_{CO}, LLF_{CO_2}, LLF_{NO_x}, LLF_{PM}, and LLF_{SO_2}	The LLF of CO, CO_2, NO_x, PM, SO_2.
$SFOC$	Special fuel oil consumption (g/kWh).
P_{AE} and P_{ME}	Installed power of AEs and MEs (kW).
MWR_{co_2}, MWR_{so_2}, and MWR_{so_4}	The ratio of the relative molecular mass of CO_2, SO_2, and SO_4, defaulted as 44/12, 64/32, and 7, respectively.
t_{berth} and t_{SP}	The total operation times of vessels while at berth and while connected to SP, respectively (h). It is collected from SP data in this paper.
$t_{AE,berth}$, $t_{AB,berth}$, and $t_{ME,berth}$	Operation times of AEs, ABs, and MEs at berth, respectively (h).
η_{SO_2} and η_{so_4}	Conversion rates of SO_2 and SO_4, defaulted as 97.753 % and 2.247 %, respectively.

time (Kotrikla et al., 2017). Such operation suggests that the MEs remain active to fulfil essential operational requirements, such as providing electrical power or maintaining the vessel's position, rather than shutting down entirely. As indicated by the results from the LA series reports on emission inventory and IMO-related reports, emissions exhibit significant increases when the ships' MEs operate under such low-load conditions. Surprisingly, these low-load MEs emissions are often neglected in estimations, especially when assessing emissions during berthing.

To address these issues, this paper proposes a new scheme that incorporates AEs, ABs, and low-load MEs to estimate the ship-at-berth emissions of CO, CO_2, NO_x, PM, and SO_2, with a particular emphasis on the role of low-load MEs during the berthing period. The foundational formula for calculating these emissions is presented in **Eq. (1)**, while the notations and definitions used in this paper are detailed in Table 3. After demonstrating the reliability of improving AEs estimation, the real SP energy consumption (EO_{SP_AE}) and duration (t_{SP}) are considered as the energy output of and duration of AEs (EO_{SP_AE} and t_{SP}, respectively). Emissions from AEs (E_{AE}) are calculated based on the real EO_{SP_AE} and the associated emissions factors (EF_{e_AE}). Emissions from ABs (E_{AB}) are determined by the load of ABs (L_{AB}), their operation time at berth ($t_{AB,berth}$), and the corresponding emissions factors (EF_{e_AB}); Emissions from low-load MEs ($EO_{ME\_low\ load}$) are computed using MCR, engine load (EL_{ME}), their operation time at berth (t_{ME}), emission factor (EF_{e_ME}), and low-load emission adjustment factor (LLF). For a detailed explanation, refer to **Eqs. (2) to (11)**.

$$E = E_{AE} + E_{AB} + E_{ME\_low\ load} \tag{1}$$

$$EO_{AE} = EO_{SP\_AE} \tag{2}$$

$$E_{AE} = EO_{SP\_AE} \times EF_{e\_AE} \tag{3}$$

$$L_{AE} = EO_{SP\_AE} / t_{SP} \tag{4}$$

$$FC_{AE} = EO_{SP\_AE} \times SFOC_{AE} \tag{5}$$

$$E_{AB} = L_{AB} \times t_{AB,berth} \times EF_{e\_AB} \tag{6}$$

$$FC_{AB} = L_{AB} \times t_{AB,berth} \times SFOC_{AB} \tag{7}$$

$$E_{ME\_lowload} = MCR \times EL_{ME} \times t_{ME} \times EF_{e\_ME} \times LLF \tag{8}$$

$$FC_{ME} = MCR \times EL_{ME} \times t_{ME} \times SFOC_{ME} \tag{9}$$

$$t_{ME,berth} = 5\% \times t_{berth} \tag{10}$$

Table 4
The comparison between the proposed method and existing methods.

Methods and parameters	Previous methods (AEs, or AEs and ABs)	Proposed method (AEs, ABs, and low-load MEs)
AEs emissions or related source data		
P_{AE}	Refer to Table 2.	EO_{SP_AE}/t_{berth}.
t_{berth}	Extracted from AIS.	Investigate from SP data.
L_{AE}	$P_{AE} \times t_{berth}$.	EO_{SP_AE}.
EF_{AE}	Default value in references.	Appendix Table A4 to Table A9.
E_{AE}	$EO_{AE} \times EF_{e\_AE}$, $FC_{AE} \times EF_{f\_AE}$ or others.	$E_{AE} = EO_{SP\_AE} \times EF_{e\_AE}$.
ABs emissions or related source data		
L_{AB}	Refer to Table 2.	Sourced from LA series reports on emission inventory (Starcrest, 2023).
EF_{AB}	Default value in references.	Appendix Table A4 to Table A8.
E_{AB}	$L_{AB} \times t_{AB,berth} \times EF_{e\_AB}$ or others.	$L_{AB} \times t_{AB,berth} \times EF_{e\_AB}$.
Low-load MEs emissions or related source data		
Low-load MEs	Neglected.	Considered.
MCR		Sea-Web ports database.
EL_{ME}		2%-20%.
t_{ME}		$5\% \times t_{berth}$.
EF_{e_ME} and LLF		Appendix Table A4 to Table A9.
$E_{ME\_low\ load}$		$MCR \times EL_{ME} \times t_{ME} \times EF_{e\_ME} \times LLF$.

$$\boldsymbol{t_{berth} = t_{SP} = t_{AE,berth} = t_{AB,berth}} \tag{11}$$

Regarding the specific parameters in this proposed method, vessel characteristics such as MCR, GT, and DWT, etc., are sourced from the Sea-Web ports. Parameters related to AEs, including EO_{SP_AE}, L_{AE}, and t_{berth}, are collected and calculated from actual SP data. Parameters for ABs, such as L_{AB}, are obtained from the annually published LA series reports on emission inventory, which offer timely updates and are widely recognised for their authoritative status (Port of Los Angeles, 2024). Fuel-related parameters, including EF_e of CO_2, SO_2, and PM, are calculated using **Eqs. (12) to (17)**. EF_{NO_x} and EF_{CO} are based on empirical data from multiple authoritative reports (EPA, 2020; IMO, 2021). The range of $SFOC$ values across various engine types and fuel categories are summarised in Appendix Table A2. It is crucial to note that this study employs a range of values for emission factors to enhance accuracy. For EF_{PM}, the value range is selected from the maximum interval derived from **Eqs. (14) to (17)**. Detailed values are provided in Appendix Table A3-Table A9.

$$EF_{CO_2} = SFOC \times C \times MWR_{co_2} \tag{12}$$

$$EF_{SO_2} = SFOC \times S \times MWR_{SO2} \times \eta_{SO_2} \tag{13}$$

HFO (IMO, 2021):

$$EF_{PM_{10}} = 1.35 + SFOC \times (S - 0.0246) \times MWR_{SO_4} \times \eta_{SO_4} \tag{14}$$

MGO (IMO, 2021)

$$EF_{PM_{10}} = 0.23 + SFOC \times (S - 0.0024) \times MWR_{SO_4} \times \eta_{SO_4} \tag{15}$$

HFO (EPA, 2020)

$$EF_{PM_{10}} = 0.5761 + SFOC \times S \times MWR_{SO_4} \times \eta_{SO_4} \tag{16}$$

MGO (EPA, 2020)

$$EF_{PM_{10}} = 0.1545 + SFOC \times S \times MWR_{SO_4} \times \eta_{SO_4} \tag{17}$$

To provide a more detailed explanation, Table 4 aid to compare the proposed method with existing methods, focusing on engine types and associated parameters. The primary principles are outlined as follows:

(1) Case studies are employed to compare results and parameters (P_{AE}, EL_{AE}, L_{AE}, FC_{AE}, SO_2, CO_2, NO_X, PM, and CO) from existing research methods with those estimated from real SP data to identify issues in current methods, verify the reliability of SP data on estimated AEs emissions, and suggest effective ways to determine ship-related parameters.

(2) Using multiple containerships with HFO as a baseline, this study demonstrates the performance of the proposed method by assessing total emissions of ship-at-berth from AEs, ABs, and low-load MEs.

(3) The proposed method is employed to evaluate the effectiveness of ten classical emission reduction strategies in the shipping industry.

With the considerations of AEs, ABs, and low-load MEs, along with the support of SP data, this proposed method more closely reflects reality and provides a comprehensive assessment of ships-at-berth emissions. It highlights the importance of collecting and processing SP, offering valuable opportunities for further research and practical applications.

Table 5
'Cosco Shipping Sagittarius' static characteristics.

Characteristics	Description	CharacteristicsiTEM	Description
Vessel name	Cosco Shipping Sagittarius	Construction year	2018
IMO No.	9783473	Newbuilding price ($)	$139,500,000
Ship type	Containership	GT	194,864
Flag	Hong Kong, China	DWT	202,133
Shipbuilder	Shanghai Waigaoqiao Shbldg	NT	115,302
Keel laid	2015/12/21	TEU	20,038
Class	CCS & DNV-GL	Reefer containers	1,000
ME		AE	
MCR	55,000	No.	4
RPM	72	MCR	3360*2
Max speed	22	MCR	4500*2
Service speed	19	AE power	15,720
Speed & consumption	22 knots &168 tons/day		

Table 6
Comparative analyses of calculation results.

Parameters	P_{AE}(MW)	EL_{AE}(%)	L_{AE}(MW)	FC_{AE}(kg)	CO_2(kg)	SO_2(kg)	PM(kg)	NO_X(kg)	CO(kg)
Actual/estimate value in this study	15.72	14 %	2.20	2,617–4,244	8,390–13,601	4–12	2–4	109–198	3–26
EO method average	10.92	54 %	4.10	3918	18,501	47	19.6	266	21.3
FC method average	35.00	46 %	8.52	12,036	40,722	459	63.8	798	124.9
FC-1	14.78	60 %	8.87	13,040	36,760	117.4	N/A	743.3	N/A
FC-2	5.75	13 %	0.75	990	3140	19.3	N/A	N/A	N/A
FC-3	5.75	50 %	2.87	3810	12,079	N/A	N/A	N/A	N/A
FC-4	39.11	19 %	7.43	9854	31,335	374.4	24.6	581.4	N/A
FC-5	12.10	19 %	2.30	3048	9694	115.8	7.6	179.9	N/A
FC-6	186.06	20 %	37.21	49,791	158,285	2688.7	333.6	3087.0	368.5
FC-7	152.86	20 %	30.57	40,905	130,037	2208.9	274.1	2536.1	302.7
FC-8	N/A	20 %	N/A	23,299	74,558	233.0	28.0	815.5	230.7
FC-9	N/A	20 %	N/A	9869	31,581	98.7	10.9	621.7	39.5
FC-10	N/A	20 %	N/A	10,556	33,780	105.6	11.6	665.1	42.2
FC-11	15.72	50 %	7.86	10,847	34,493	412.2	27.1	640.0	N/A
FC-12	12.16	18 %	2.19	2849	N/A	27.8	4.2	182.5	14.4
FC-13	1.00	100 %	1.00	1200	3870	12.0	N/A	78.0	N/A
FC-14	7.00	100 %	7.00	9240	N/A	N/A	41.2	N/A	117.6
FC-15	1.40	100 %	1.40	1554	4982	2.1	1.4	88.1	4.0
FC-16	1.32	100 %	1.32	1719	5510	4.5	1.8	150.0	4.8
EO-1	15.72	17 %	2.67	N/A	10,882	2.6	2.9	167.0	17.6
EO-2	15.72	50 %	7.86	10,847	32,823	40.1	37.7	646.1	N/A
EO-3	1.00	100 %	1.00	1200	3870	12.0	N/A	78.0	N/A
EO-4	7.00	100 %	7.00	9240	N/A	N/A	41.2	N/A	117.6
EO-5	17.28	100 %	17.28	N/A	69,984	218.8	14.5	342.1	N/A
EO-6	38.97	40 %	15.59	N/A	65,474	43.0	28.1	1103.7	N/A
EO-7	5.50	40 %	2.20	2825	9108	N/A	4.0	N/A	N/A
EO-8	11.55	50 %	5.78	7415	23,909	N/A	10.4	N/A	N/A
EO-9	39.11	19 %	7.43	9854	30,797	189.0	21.8	619.8	49.0
EO-10	12.10	19 %	2.30	3048	9528	58.5	6.8	191.7	15.2
EO-11	12.10	19 %	2.30	3048	43.7	N/A	N/A	N/A	N/A
EO-12	12.16	18 %	2.19	2849	N/A	27.8	4.2	182.5	14.4
EO-22	N/A	N/A	N/A	N/A	N/A	15.6	195.1	372.4	N/A
EO-13	5.75	15 %	0.86	1500	N/A	22.2	1.6	71.9	5.7
EO-14	13.50	17 %	2.30	3994	N/A	59.2	4.1	191.4	15.1
EO-15	11.98	18 %	2.16	3752	8837	28.6	4.9	158.1	14.2
EO-16	1.04	100 %	1.04	1804	4250	13.8	2.3	76.0	6.8
EO-17	1.40	100 %	1.40	2436	5762	19.3	3.2	88.2	9.2
EO-18	3.46	19 %	0.66	1719	9528	29.2	2.5	191.7	15.2
EO-19	1.32	100 %	1.32	1719	5510	16.8	2.6	61.0	8.7
EO-20	1.40	100 %	1.40	1554	N/A	N/A	1.5	94.1	4.5
EO-21	1.32	100 %	1.32	1719	5713	4.7	1.8	155.5	4.9

4. Case studies and analysis

Building upon screening and classification, case studies shed light on the differences in results stemming from existing methods and SP data. Then, the proposed method is utilised to verify the role of ABs and low-load MEs in the ship-at-berth emissions. Additionally, it is used to assess the efficacy of 10 emission reduction measures across five different pollutants.

Table 7
Statistical analyses of calculation results.

	No. of Samples	Mean	Max	Min	Range	Variance	CVs
P_{AE}(kW)	34	20,129	186,064	1000	185,064	1,560,425,065	1.96
EL_{AE}(%)	37	51%	100%	13%	87%	13%	0.73
L_{AE}(kW)	34	5789	37,213	657	36,556	67,796,634	1.42
FC_{AE}(kg)	34	7738	49,791	990	48,800	115,819,848	1.39
SO_2(kg)	31	233	2689	2	2687	375,308	2.55
CO_2(kg)	30	28,871	158,285	44	158,241	1,409,331,064	1.3
NO_X(kg)	31	489	3087	61	3026	465,912	1.4
PM(kg)	32	36	334	1	332	6182	2.17
CO(kg)	23	62	368	4	364	10,360	1.65

Table 8
Recommended references matching aligning with narrower estimates.

Pollutants	FC methods in reference	EO methods in references
FC_{AE}	FC-3, 5, 12.	EO-7, 10, 11, 12, 14, 15, 17.
SO_X	FC-13, 16.	EO-3, 21.
PM	FC-12, 16.	EO-1, 7, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21.
CO_2	FC-3, 5.	EO-1, 7, 10, 15, 18.
CO	FC-9, 10, 12.	EO-1, 9, 10, 12, 14, 15, 17, 18, 19.
NO_X	FC-5, 12, 16.	EO-1, 10, 12, 14, 15, 18.

4.1. Case studies

4.1.1. Case 1: A single containership

It presents a case study of the 'Cosco Shipping Sagittarius', which consumed 13,200 kWh of electricity over a six-hour stay at a port (China Shipowners' Association, 2019). According to the Sea-web ports database, Table 5 shows the static characteristics of the identified vessel, which are employed in the 37 identified methods and improved AEs estimation with SP data to calculate the ship's emissions during its berthing period. The results are presented in Table 6.

(1) Analysis of characteristics of existing AEs emission estimation methods.

Table 7 displays statistical analyses of the calculated results across multiple variables, including P_{AE}, EL_{AE}, L_{AE}, FC_{AE}, SO_2, CO_2, NO_X, PM, and CO. Notably, P_{AE} is a critical input variable with a high Coefficient of Variation (CV), indicating significant variability compared to EL_{AE}, FC_{AE}, and L_{AE}. This suggests the substantial impact of P_{AE} on emission results. Conversely, EL_{AE} has the lowest CV, suggesting the highest consistency. FC_{AE} and L_{AE} also display relatively consistent levels, as evidenced by their CVs. The inclusion of EL_{AE} has contributed to adjusting the dispersion levels and enhancing the accuracy of the results.

Regarding pollutant estimations, CVs can be divided into three groups based on their variability and influencing factors. The first group, with high CVs, includes CV_{SO_2} and CV_{PM}, significantly affected by sulphur content in fuel. The second group, displaying more consistent CVs, comprises CV_{NO_X} and CV_{CO_2}, with CVs slightly lower or equal to those for $CV_{L_{AE}}$ and $CV_{FC_{AE}}$. The third category, represented by CV_{CO}, influenced by engine-related factors, falls between the first two groups in variability. In summary, CV_{SO_2} is the highest, followed by PM, highlighting the importance of sulphur content in fuel to the larger CVs. As efforts on reduction NO_X emissions and refinement EF continue, variations in NO_X dispersion can be expected in the future, as evidenced by this analysis.

Combining Table 6 and Table 7 reveals the following key findings: 1) The average estimates from all methods tend to exceed those calculated using actual SP data significantly. The overestimation varies widely, ranging from 1.28 to 20 times the actual values. 2) For most parameters, except for EL_{AE}, the average estimates derived from FC methods are notably higher than those from EO methods. These discrepancies span from 2.08 to 9.77 times, consistent with the findings of previous studies by Lopez-Aparicio et al. (2017) and Lee et al. (2021). 3) Utilising the fuel-related parameters from Section 3 results in much narrower estimated value ranges compared to other methods, indicating these selected parameters provide more accurate and reliable estimates. 4) Consistent with the previously discussed CV groups, the estimated values of CO_2 and NO_X are more stable than those for SO_2, PM, and CO. 5) The estimated output indicators, such as SO_2, CO_2, NO_X, PM, and CO, show much greater fluctuations than the input or intermediate parameters, indicating a higher potential for estimation errors. This stability can be attributed to the varying emission factors and differences in engine types. These findings underscore the complexity of estimating ship emissions during berthing, which is influenced by a multitude of factors.

(2) Comparative analyses to determine associated parameters, demonstrate the reliability of SP data, and identify reliable existing methods.

In terms of the estimated P_{AE}, Table 2 outlines methods for its determination. Notably, the multiple regression analysis employed by Gutierrez-Romero et al. (2019) typically yields significantly higher estimates than other methods. In contrast, methods based on the average or default values for specific ship types, as used by Wang et al. (2007b) and Jalkanen et al. (2009), tend to produce lower estimates. Staged regression has been demonstrated to be more accurate than non-staged fitting (Gligor et al., 2021). Empirical data collected from surveys and shipyards generally provides the most precise estimates. Hence, this paper recommends employing a staged fitting method for determining P_{AE}, emphasising the importance of thorough comparison with officially announced ship stage data, as

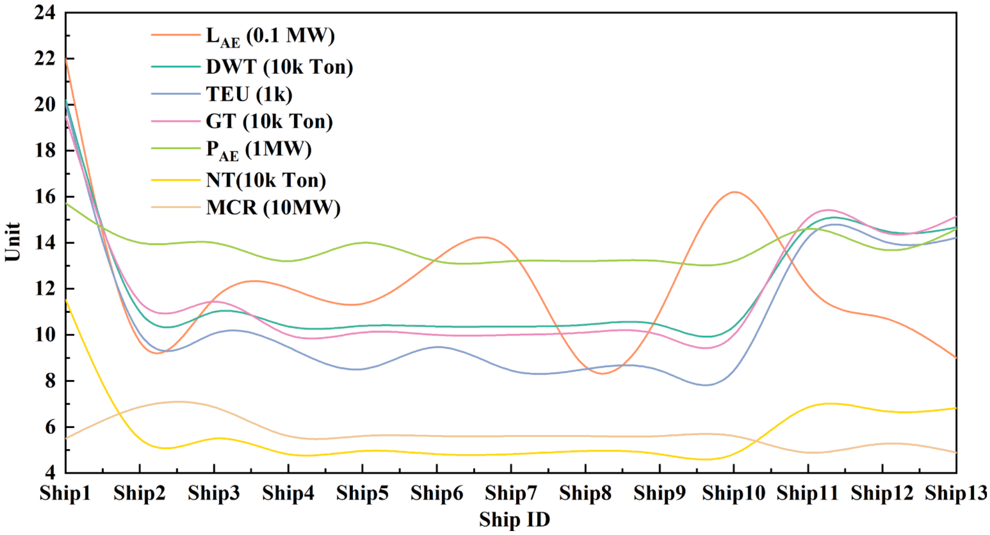


Fig. 3. Trend analysis of multi-indicator relationships.

Table 9
Comparative analysis of total estimated pollution emissions.

Emissions (kilograms)	Estimated range in existing methods					Estimated in this study
	Estimated range	Mean	CVs	FC method average	EO method average	
SO_2	[22.84, 13830]	1673	1.80	3033	553	[23.61, 57.43]
PM	[15.00, 2661]	292	1.92	401	227	[15.87, 19.06]
NO_X	[601.92, 33102]	4810	3.40	7707	2718	[601.92, 15879]
CO_2	[39868, 1681353]	284,893	1.18	388,345	194,373	[55407, 67367]
CO	[43.17, 17662]	1235	2.88	2732	337	[50.45, 102.78]

suggested by Yu et al. (2019), to enhance the accuracy of forecasted P_{AE}. As shown in Table 6, the estimation of EL_{AE} during ship berthing in port has often been either overlooked or assigned a default value of 1 in recent studies. An increasing number of researchers are adopting this default approach, adjusting it for specific ship types and operational modes (Sciberras et al., 2016; Faber et al., 2020). This approach has led to a wide variability in EL_{AE} estimates, from 13% to 100%. Generally, EL_{AE} values during the berthing period fall within the 15–20% range, aligning closely with the estimated EL_{AE} of 14% for 'Cosco Shipping Sagittarius'. This suggests this range is a more accurate guideline for future research. The overall estimation of L_{AE} in Table 7 is relatively consistent and reflects actual operational conditions, with values ranging from 0.66 MW to 37.21 MW. These differences are influenced by variations in P_{AE} and EL_{AE}. Inaccuracies in either parameter lead to estimation discrepancies. For instance, Gutierrez-Romero et al. (2019) encounter errors due to inaccuracies in P_{AE} estimation, while Sciberras et al. (2016) neglect EL_{AE}, resulting in errors in L_{AE} estimation.

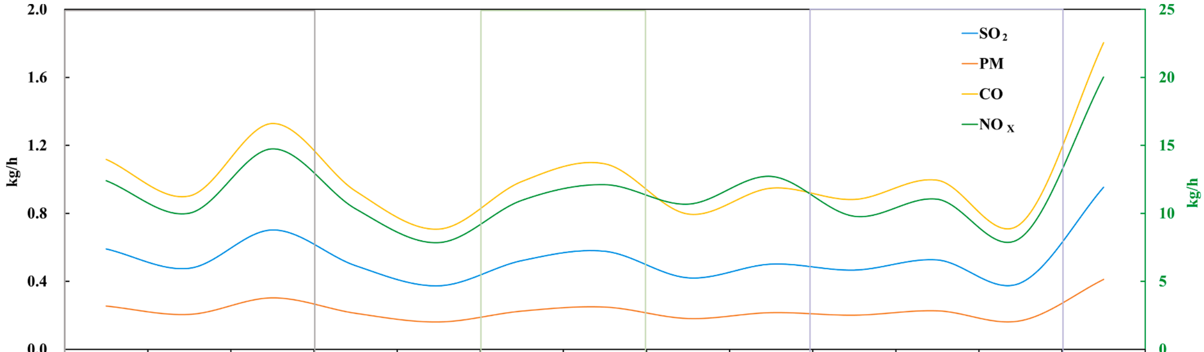
Table 8 highlights recommended references where the results align with the narrower estimates of FC_{AE} and emissions proposed in this study. These results are supported by authoritative research, such as Smith et al. (2015), EPA and ICF (2009), and Starcrest (2021), affirming the reasonableness and validity of the proposed method. Estimates of emissions vary widely depending on the methods, parameters, and pollutants considered, with some methods yielding significantly higher estimates. However, the estimates derived by the ranges of emission factors and real SP energy consumption data in this study exhibit much narrower ranges and greater consistency.

4.1.2. Case 2: Multiple containerships

The study collects data on 13 containerships during their SP connections from online and surveys, as presented in Appendix Table A10, to analyse the results of multiple containerships analysis. Appendix Table A11 displays their static characteristics, with ship size ranging from 8,452 to 20,038 TEU and keel laying dating from 2007 to 2015. These ships are equipped with 800 to 1,000 TEU slots for refrigerated containers, accounting for approximately 5% to 11% of their total capacity.

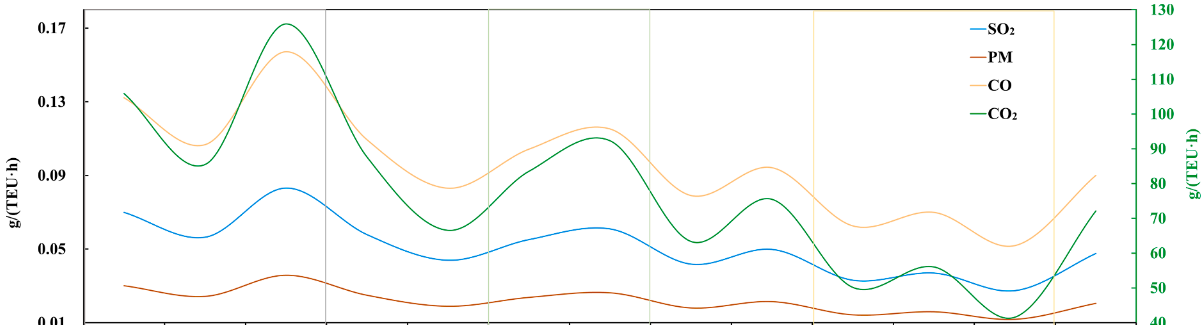
(1) Analysis of characteristics of existing AEs emission estimation methods.

Firstly, a trend analysis in Fig. 3 reveals the initial findings. Notably, GT, DWT, NT, and TEU exhibit strong correlations with each other, but their correlations with MCR, P_{AE}, and L_{AE} are relatively weaker. P_{AE} is stable and shows low volatility, displaying a phased correlation with MCR. The relationship between L_{AE} and P_{AE} is not significant, indicating that L_{AE} is primarily influenced by ship type and operational mode (Starcrest, 2021). To understand these findings better, further research with more data and advanced analysis is needed.



	Ship 7 (8452 TEU)	Ship 9 (8452 TEU)	Ship 10 (8452 TEU)	Ship 5 (8508 TEU)	Ship 8 (8508 TEU)	Ship 4 (9466 TEU)	Ship 6 (9466 TEU)	Ship 2 (10060 TEU)	Ship 3 (10060 TEU)	Ship 12 (14080 TEU)	Ship 11 (14200 TEU)	Ship 13 (14200 TEU)	Ship 1 (20038 TEU)
SO_2	0.59	0.48	0.70	0.49	0.37	0.52	0.58	0.42	0.50	0.47	0.53	0.39	0.95
PM	0.25	0.21	0.30	0.21	0.16	0.22	0.25	0.18	0.22	0.20	0.23	0.17	0.41
CO	1.12	0.90	1.33	0.93	0.71	0.99	1.09	0.80	0.95	0.88	0.99	0.74	1.80
NO_X	12.40	10.01	14.74	10.33	7.84	10.95	12.11	10.67	12.72	9.78	11.04	8.19	20.02

Fig. 4. Investigation into the correlation between ship size and emissions.



	Ship 7 (8452 TEU)	Ship 9 (8452 TEU)	Ship 10 (8452 TEU)	Ship 5 (8508 TEU)	Ship 8 (8508 TEU)	Ship 4 (9466 TEU)	Ship 6 (9466 TEU)	Ship 2 (10060 TEU)	Ship 3 (10060 TEU)	Ship 12 (14080 TEU)	Ship 11 (14200 TEU)	Ship 13 (14200 TEU)	Ship 1 (20038 TEU)
SO_2	0.07	0.06	0.08	0.06	0.04	0.06	0.06	0.04	0.05	0.03	0.04	0.03	0.05
PM	0.03	0.02	0.04	0.02	0.02	0.02	0.03	0.02	0.02	0.01	0.02	0.01	0.02
CO_2	0.13	0.11	0.16	0.11	0.08	0.10	0.12	0.08	0.09	0.06	0.07	0.05	0.09
CO	105.91	85.51	125.93	87.66	66.57	83.55	92.35	63.38	75.50	50.16	56.05	41.58	72.13

Fig. 5. Comparison of emissions across various ship sizes (g/(TEU·h).

Appendix Table A12 shows the descriptive statistics of outcomes derived from the existing methods. In addition to the findings in Case 1, Case 2 reveals that the *CVs* vary by ship size, with large ships showing higher *CVs*. However, the average among multiple containerships could lower their *CVs*, indicating that an increase in the number of vessels could reduce discrepancies in the estimation and enhance the accuracy. Table 9 provides a comparative analysis of total estimated emissions from the 13 investigated containerships between existing methods and improved estimations based on SP data. This analysis indicates a significant disparity in emissions. As observed in Case 1, by application of emission factors with a range of values and the actual L_{AE}, the estimated emissions are much narrower, aligning closely with results from the LA series reports on emission inventory, as well as EPA (2020) and IMO (2021). This alignment provides strong evidence of the reliability of the proposed method and emission factors.

The link between ship size and emissions reveals an intriguing pattern (see Fig. 4 and Fig. 5). As ship size increases, both emissions per hour (Fig. 4) and emissions per TEU per hour (Fig. 5) initially decrease and then rise. This trend is relatively stable for ships in 8,455–9,466 TEU. From 10,000 to 14,200 TEU, there is a noticeable drop in emissions per unit, followed by a significant rise at 20,000 TEU. For instance, SO_2 emissions range from 0.04 to 0.08 g/(TEU·h) for ships between 8,452 and 10,060 TEUs, drop further to 0.03 to 0.04 g/(TEU·h) for 14,080 TEU ships, but rise to 0.05 g/(TEU·h) for 20,038 TEU ships. This indicates a complex correlation between ship size and emissions per unit. Ships in the 10,000 to 14,000 TEUs range demonstrate the highest efficiency in emissions, while ships outside this range, both smaller and larger, are less efficient. This insight is vital for comprehending the environmental footprint of maritime shipping and guiding decisions regarding fleet composition and cargo transportation methods to reduce emissions.

(2) Comparative analyses to determine associated parameters, demonstrate the reliability of SP data, and identify reliable existing methods.

The average estimated P_{AE} for multiple containerships is approximately 23% lower than the actual values. For Ships 11, 12, and 13, the error margin is even smaller, confirming the relationship between the methods and ship size in estimating P_{AE}, and emphasising the

Table 10
Categories of estimated P_{AE}, L_{AE}, and FC_{AE}.

Estimated parameter	Category	Reference code	Primary method	Estimated ranges	The mean of actual values
P_{AE}(kW)	I	FC-6, FC-7.	Multiple regression by TEU and GT.	[57566, 81352]	13,778
	II	EO-6, FC-4, EO-9.	Power-to-Tonnage Ratio.	[23493, 24193]	
	III	FC-1, FC-11, EO-1, EO-2, EO-14, FC-12, EO-12, FC-5, EO-10, EO-11, EO-18, EO-5 EO-8.	Empirical data, the latest published table lookup data, and staged fitting.	[11877, 14120]	
	IV	FC-3, FC-2, EO-13, EO-7, FC-14, EO-4.	Average or defaulted P_{AE} of containerships.	[4755, 5747]	
	V	FC-15, EO-20, EO-17, FC-16, EO-21, EO-19, EO-16, FC-13, EO-3.	Outdated published table lookup data, or misunderstanding with L_{AE}.	[1000, 1204]	
L_{AE}(kW)	I	FC-6, EO-5, FC-7, EO-6, FC-1.	High P_{AE}.	[8472, 16271]	1241
	II	EO-8, FC-11, EO-2.	High P_{AE} or high L_{AE}.	[6889, 7127]	
	III	FC-14, EO-4, FC-4, EO-9.	Reasonable P_{AE} and EL_{AE}.	[4464, 4756]	
	IV	FC-3, FC-5, EO-10, EO-11, EO-18, EO-1, EO-7, FC-12, EO-12, EO-15, EO-14.	More reasonable P_{AE} and matching EL_{AE}.	[2025, 2874]	
	V	FC-15, EO-20, EO-17, FC-16, EO-21, EO-19, EO-16, FC-13, EO-3, EO-13, FC-2.	Empirical data without considered P_{AE} and EL_{AE}.	[747, 1204]	
FC_{AE}(ton)	I	FC-9, FC-8, FC-7, FC-6, FC-1.	High L_{AE} or high $SFOC_{AE}$.	[12.00, 40.42]	[1.33, 1.62]
	II	EO-2, EO-8, FC-11	High L_{AE}.	[9.30, 9.34]	
	III	FC-10, FC-14, EO-4, FC-4, EO-9.	Reasonable P_{AE}, EL_{AE}, and $SFOC_{AE}$.	[5.54, 6.47]	
	IV	FC-3, EO-15, EO-14, FC-5, EO-10, EO-11, EO-18, FC-12, EO-12, EO-7.	More reasonable P_{AE} and matching EL_{AE} and $SFOC_{AE}$.	[2.97, 3.72]	
	V	EO-17, EO-16, EO-13, FC-16, EO-21, EO-19, FC-15, EO-20, FC-13, EO-3, FC-2.	Empirical data.	[0.97, 1.85]	

Table 11
Suggested approaches for establishing relevant parameters.

Parameters	Proposed FC methods	Proposed EO methods
P_{AE}	F-1, 5, 11, 12.	EO-1, 2, 5, 8, 10, 11, 12, 14, 15, 18.
EL_{AE}	F-5, 12.	EO-1,10,11,12,14,15,18.
L_{AE}	F-2, 3, 4, 5, 12, 13, 14, 15, 16.	EO-1,3,4,7,9,10,11,12,13,14,15,16,17,18,19,20,21.
$SFOC$	F-13, 15, 16.	EO-3,13,16,17,19,20,21.
EF_{SO_2}	F-15,16.	EO-1,21.
EF_{CO_2}	F-13, 15,16.	EO-3,16,17,19,21.
EF_{PM}	F-15, 16.	EO-13,19,20,21.
EF_{NO_X}	F-13, 15.	EO-3,13,16,17,19,20.
EF_{CO}	F-15,16.	EO-13,16,17,19,20,21.

importance of considering size-related variations within the same ship type. The estimation of L_{AE} is often much higher than the SP energy consumption (EO_{SP_AE}), except for using either a reasonable P_{AE} with a matching EL_{AE}, or empirical data. The same trend is observed for FC_{AE}, though it is more stable than L_{AE}. Table 10 categories the estimated P_{AE}, L_{AE}, and FC_{AE} based on different methods. The methods for determining P_{AE}, L_{AE}, and FC_{AE} identified in Case 1 are grouped into suitable categories for accurate estimation. However, other methods may either underestimate or overestimate P_{AE}, L_{AE}, and FC_{AE}. The results for multiple containerships regarding associated parameters are consistent with Case 1 but show lower fluctuations. Furthermore, it is essential to highlight that emissions at berth are influenced by numerous factors, leading to notable variations even among ships of the same size or within the same report series (Starcrest, 2011; Starcrest, 2021; EPA and ICF, 2009; EPA, 2020). Building upon the analysis, this paper has identified methods that offer relatively reliable estimates for ship-at-berth emissions. These selected methods are proven to be effective and valuable references for future research, as outlined in Table 11.

4.2. Analysis of the proposed method and its application

After the establishment of ECA and the 2020 sulphur cap, alternative fuels/measures along with HFO are used for most maritime vessels. Hence, this paper utilises HFO as a benchmark to analyse the impacts of transitioning to different fuels on various outcomes derived from the proposed method. To ensure accuracy, these analyses utilise data from multiple containerships and calculate the average of each estimation to evaluate the results. The research integrates estimations and relevant parameters, including 5 types of pollutants (i.e., CO_2, CO, NO_X, SO_2, and PM), alongside 10 kinds of emission reduction measures (i.e., MGO, LSHFO, ECA, Outside-ECA, HFO and Scrubber, HFO and SP, MGO and SP, LSHFO and SP, ECA and SP, and Outside-ECA and SP), enabling thorough analyses. The study provides an exhaustive examination of total fuel consumption, total emissions, and the emissions of each specific pollutant from different engines per containership during berthing. Detailed outcomes for each ship type and every emission reduction

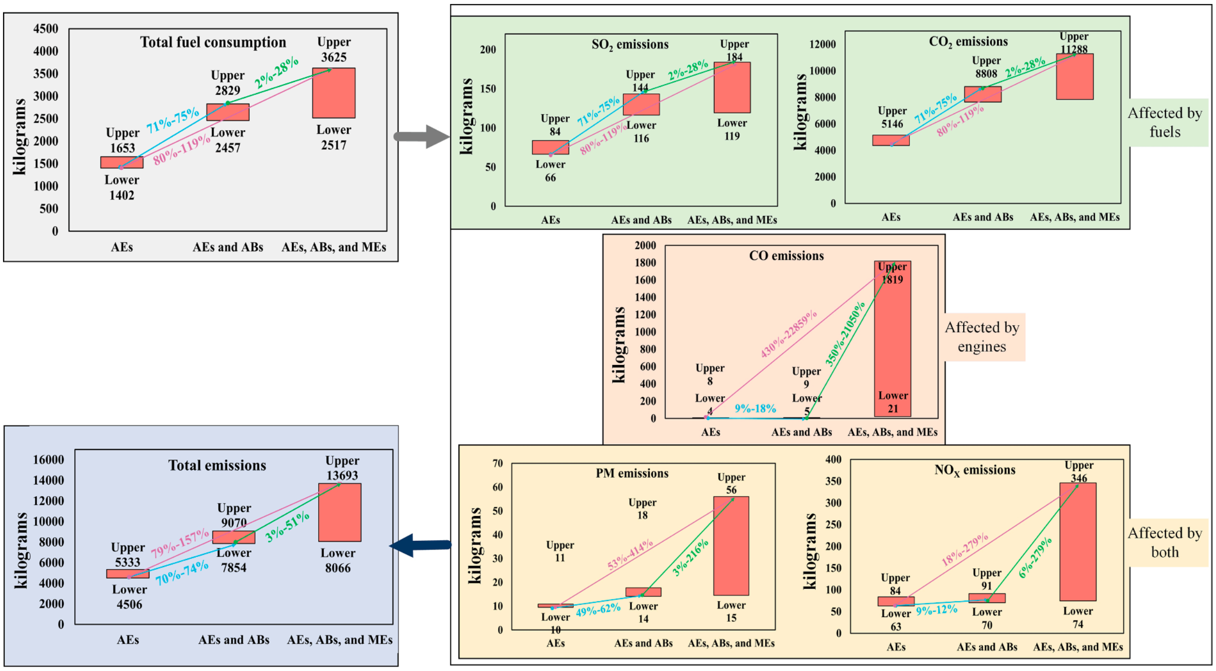


Fig. 6. Results of total fuel consumption and emissions when using HFO alone.

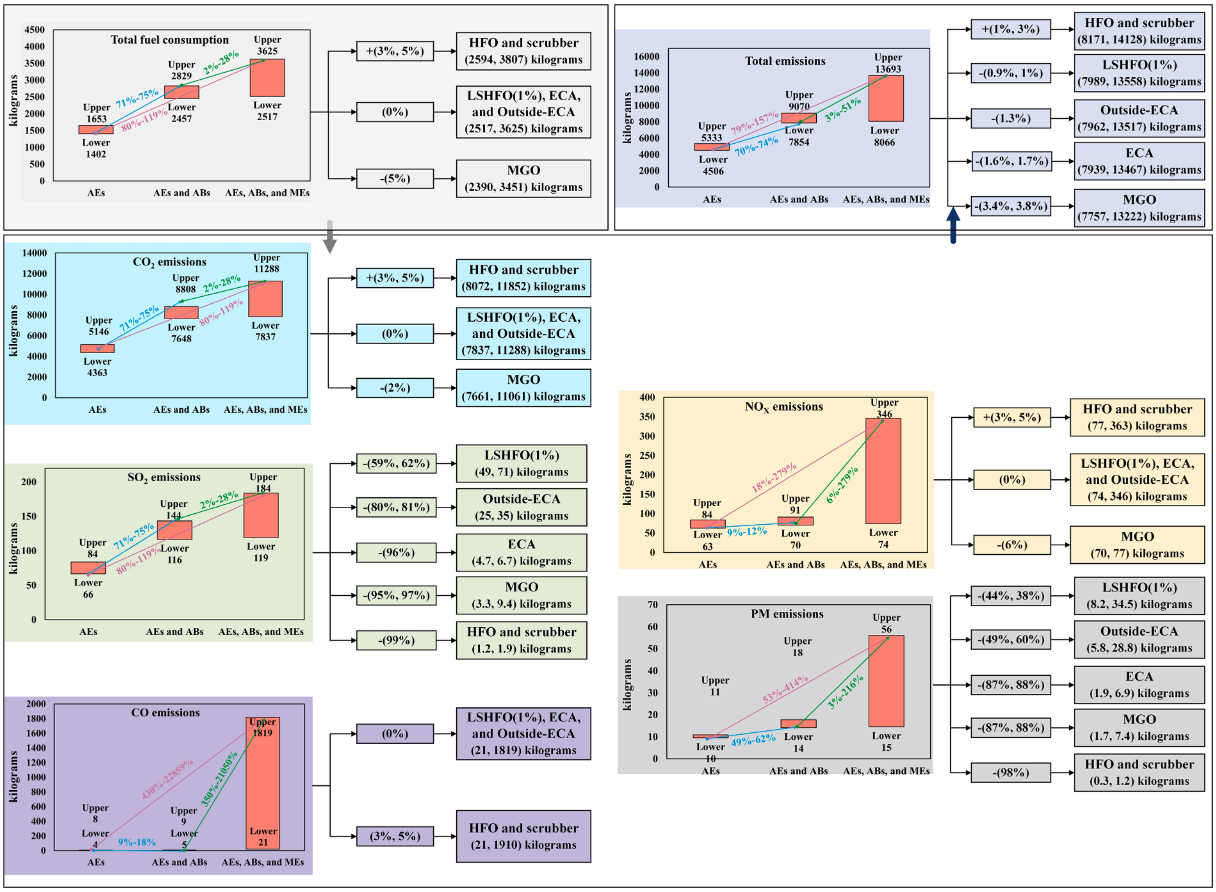


Fig. 7. Comparison of emission reduction measures without SP involving AEs, ABs, and MEs.

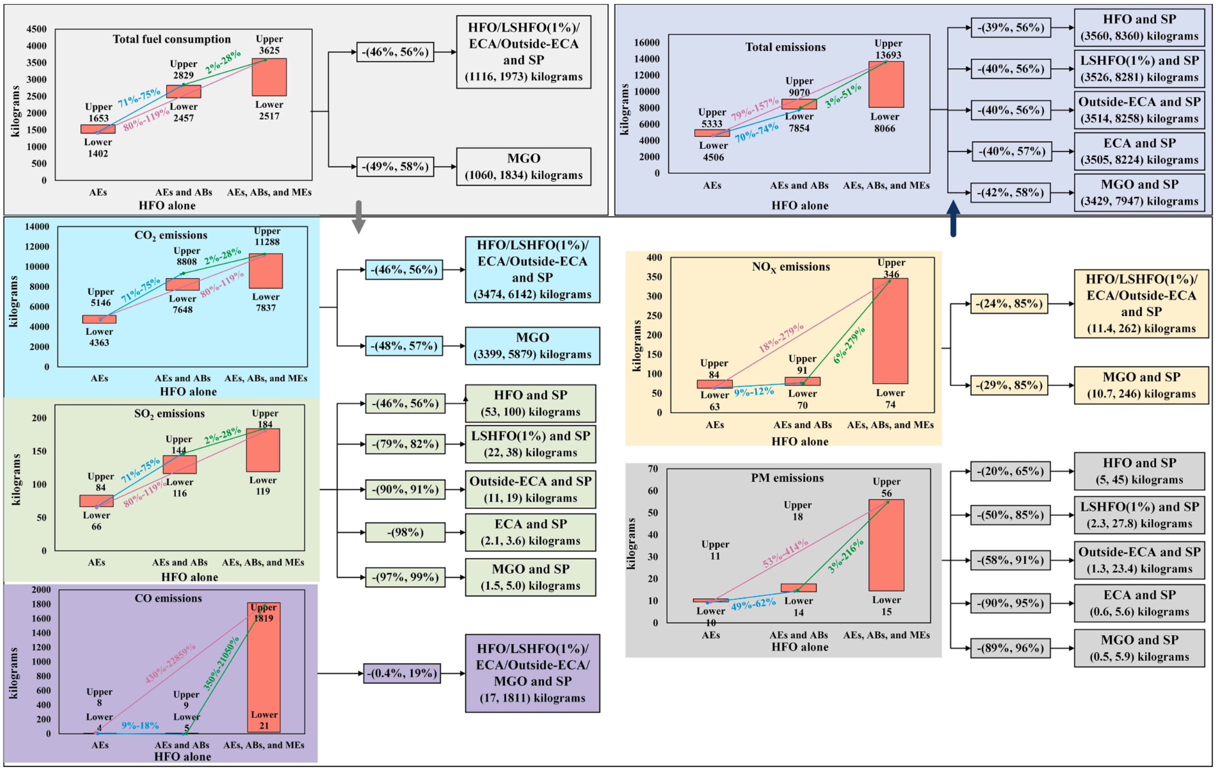


Fig. 8. Comparison of emission reduction measures with SP involving AEs, ABs, and MEs.

measure are presented in Figs. 6-8. To assess the effectiveness of SP in reducing emissions, this paper categorises these emission reduction measures into two groups: with SP and without SP, allowing for a detailed analysis of each measure.

4.2.1. *The results of HFO as the benchmark fuel*

Results of total fuel consumption and emissions when using HFO are shown in Fig. 6. It reveals that the total fuel consumption from HFO is significantly higher (by 80–119%) than those from AEs alone and slightly higher (by 2–28%) than the combined AEs and ABs in each containership. Affected by the concentrations of carbon and sulphur in the fuel, the emissions of CO_2, and SO_2 follow the same trend as total fuel consumption when taking into account AEs, ABs, and MEs. Moreover, CO emissions are 430–22,859 % above those from AEs alone and 350–21,050 % higher than from the combined AEs and ABs, due to the contributions of engine load. Similarly, influenced by both the sulphur concentrations in fuel and engine load, PM and NO_X emissions significantly exceed those from AEs alone by 53–414% and 18–279%, respectively. Compared to the combination of AEs and ABs, these emissions are still remarkably higher (by 3 %-216% for PM and 6–279% for NO_X). Consequently, the total emissions from HFO are 79–157% higher than those from AEs alone and 3–51% higher than from the combined AEs and ABs, underscoring the critical roles of ABs and MEs in energy consumption during berthing and emphasising the importance of their impact, especially for CO and NO_X emissions. Regarding pollutants, CO_2 emissions account for 84%-97% of total emissions, followed by SO_2 which remains within a stable range of 1.34–1.48%. PM emissions are the lowest, ranging between 0.18% and 0.41%. With influences from low-load MEs, NO_X and CO emissions constitute 0.92–2.53% and 0.26–13.28%, respectively, with a notably wide range. Additionally, both MEs and AEs are significant sources of NO_X emissions, with factors such as the engine's keel laying time, engine type, and fuel type resulting in complex outcomes. Although NO_X emissions currently represent a relatively small proportion, their impact on environmental and human health is substantial, comparable to that of SO_2. With increasing awareness, the industry is likely to focus more on reducing NO_X emissions in the future.

4.2.2. *Assessment and analysis of emission reduction measures without SP*

When evaluating different emission reduction measures without SP in comparison to HFO, it is evident that the use of HFO with scrubbers effectively meets sulphur emission limits, significantly reducing SO_2 and PM emissions by 99% and 98%, respectively (see Fig. 7). However, this measure leads to increased total fuel consumption and higher emissions of CO_2, CO, and NO_X, ultimately resulting in an overall increase in total emissions, indicating its lack of environmentally friendly. Conversely, switching to LSHFO, Outside-ECA-compliant, and ECA-compliant fuel maintains similar fuel consumption, CO_2, CO, and NO_X levels as HFO, but the lower sulphur content in these alternative fuels significantly decreases SO_2 and PM emissions by 59–62% and 38–44% for LSHFO, 80–81% and 49–60% for Outside-ECA-compliant oil, and 96% and 87–88% for ECA-compliant fuel, respectively.

As a result, total emissions from each containership decrease by 1% for LSHFO and Outside-ECA-compliant oil and 1.6% for ECA-compliant oil. Additionally, shifting to MGO also results in a substantial reduction in SO_2 and PM emissions by 95–97% and 87%, respectively, and slightly lower other metrics, including fuel consumption, total emissions, CO_2, CO, and NO_X, by 2–6%. These alternatives thus offer sustainable emission reduction measures for containerships, balancing environmental impact with operational needs.

4.2.3. Assessment and analysis of emission reduction measures with SP

When combining SP with alternative fuels such as HFO/LSHFO/Outside-ECA and ECA fuel oil, the total fuel consumption and emissions from ABs and low-load MEs will be the same as those from HFO alone. The fuel consumption and CO_2 emissions of SP with HFO/LSHFO/Outside-ECA and ECA fuel will be 46–56% less than the baseline of using HFO alone, 0.4–19% for CO emissions, and 24–85% for NO_X emissions (see Fig. 8). Employing HFO with SP reduces SO_2 emissions by 46–56%, while LSHFO with SP can yield a reduction of 79–82%. Furthermore, Outside-ECA, ECA-complaint oil, and MGO with SP achieve reductions exceeding 90%. Regarding PM emissions, HFO with SP cuts PM emissions by 20% to 65%. Compliant fuel outside ECA post-2020 with SP can lead to a reduction of more than 60–90%, while MGO with SP achieves a reduction of over 90%.

The comparative analysis of the application results provides a comprehensive examination of how emission reduction measures affect vessel emissions. It highlights the critical roles of ABs and MEs in energy consumption and emissions during berthing, emphasising the need for the maritime industry to address NO_X emissions. Switching to LSHFO, ECA-compliant, and Outside-ECA-compliant fuel, as well as MGO, results in comparable fuel consumption and CO_2 levels as HFO but significantly reduces SO_2 and PM emissions. Additionally, using HFO with scrubbers meets sulphur emission limits but leads to increasing total emissions and fuel consumption. The combination of SP with alternative fuels demonstrates the potential for substantial emission reductions, underscoring the importance of adopting diverse emission reduction measures to mitigate the environmental impact of ship berthing activities.

4.3. Implications

The innovative analysis results reveal broad implications that could guide the future development of measures for minimising emissions from containerships at berthing. From an application perspective, it underscores the environmental benefits of various emission reduction measures, thereby accelerating the promotion of SP. By calculating the costs of installation, maintenance, operation, and labour, alongside the benefits of fuel savings, incentives, potential revenue from reduced emissions, improvements in human health, and enhanced reputation, the integration emissions and cost-benefit analysis enables shipping companies to select the optimal strategy for facilitating the industry's adaptation to evolving energy landscapes and regulatory shifts focused on curbing emissions. For port authorities, the findings offer essential empirical evidence to enhance understanding of ship-at-berth emissions and support informed policy-making, especially regarding the implementation of SP. This could stimulate increased SP-related initiatives, management, and emission reduction efforts. Policymakers and other related stakeholders can employ these findings, including the new methodology, to harness the impact of ship-at-berth emissions on local air quality and the health benefits associated with emission reductions. Such insights will aid in prompt strict emissions controls and a wide adaptation of green technologies in the shipping industry, hence fertilising global shipping practices and environmental outcomes.

Methodologically, the incorporation of SP data into ship-at-berth emission methods offers a novel scheme for studying the characteristics of AEs and estimating ship-at-berth emissions. The proposed method can be extended to investigate ship-at-berth emissions from AEs, ABs, and low-load MEs for large ship fleets and other ship types, following further validation and potential adaptation, provided SP data is available. Instead of mining AIS data to identify berthing operational mode and times, this method could directly utilise SP data, vessel characteristics, and the LA series reports on emission inventory to calculate ship-at-berth emissions, significantly reducing the computation cost. With the newly compiled dataset on SP, future researchers can use data fusion, machine learning and optimisation algorithms to explore the relationships between emissions and their influence factors, thereby advancing the research process related to ship emissions. The results will contribute to the growing body of knowledge on maritime emissions, providing a foundation for future research and innovation.

Taking into account these advancements, ship-at-berth emissions can be accurately estimated using enhanced and expanded approaches. For instance, by incorporating detailed berthing information, emissions can be precisely calculated based on berth specifics, air monitoring of ships while in port, crane handling efficiency, and the analysis of ships' static and dynamic characteristics.

Moreover, as SP serves as a vital interface for energy transfer between ports and vessels, it will continue to receive increasing attention in the coming years. This review of influencing factors, methodologies, statistics, and comparative analysis could facilitate the estimation of emissions when renewable energy sources (such as photovoltaics, wind, hydrogen, batteries, and energy storage) supply power to SP throughout a complete lifecycle assessment. This assists in accelerating the transition to a green maritime industry and implicates the energy management of ships and ports.

4.4. Future research directions

According to the literature review, methods, case studies, and implications, to synthesise the various insights and recommendations outlined in the analysis, the following points could emerge as critical areas on the future research agenda in the field of ship emissions:

4.4.1. Unified ship emission database

The major sources of information on ship-related emissions are the global ship emissions provided by IMO and Los Angeles port's

Table A1
Literature and associated literature code.

Reference Code	Reference	Reference Code	Reference
FC-1	Gligor et al. (2021)	EO-4	Jalkanen et al. (2012)
FC-2	Wang et al. (2007a)	EO-5	Sciberras et al. (2016);Yu et al. (2019)
FC-3	Lu and Huang (2021)	EO-6	Adamo et al. (2014)
FC-4	Lee et al. (2021)	EO-7	Kotrikla et al. (2017)
FC-5	Lee et al. (2021)	EO-8	Kotrikla et al. (2017)
FC-6	Gutierrez-Romero et al. (2019)	EO-9	Lee et al. (2021)
FC-7	Gutierrez-Romero et al. (2019)	EO-10	Lee et al. (2021)
FC-8	Hickman et al. (1999)	EO-11	Lu and Huang (2021)
FC-9	Trozzi and Vaccaro (2006)	EO-12	Yang et al. (2021)
FC-10	Trozzi and Vaccaro (2006)	EO-13	Starcrest (2005)
FC-11	Cooper and Gustafsson (2004b)	EO-14	Starcrest (2007)
FC-12	Yang et al. (2021)	EO-15	Starcrest (2008)
FC-13	Jalkanen et al. (2009)	EO-16	Starcrest (2011)
FC-14	Jalkanen et al. (2012)	EO-17	Starcrest (2021)
FC-15	Faber et al. (2020)	EO-18	EPA and ICF (2009)
FC-16	Smith et al. (2015)	EO-19	EPA (2020)
EO-1	Jian et al. (2017)	EO-20	Daniel et al. (2023)
EO-2	Cooper and Gustafsson (2004b)	EO-21	Smith et al. (2015)
EO-3	Jalkanen et al. (2009)		

Table A2
Range of $SFOC_{Base}$ value (g/kWh).

Engine type	Fuel type	Range of $SFOC_{Base}$
ME	HFO	175–230
	MGO/MDO	165–210
AE	HFO	195–230
	MGO/MDO	185–225
AB	HFO	305–340
	MGO/MDO	290–320

Table A3
Effect of EL on *SFOC*.

Reference	EL	*SFOC*	
		4-Stroke	2-Stroke
Styhre et al. (2017)	>50 % MCR	nominal	nominal
	25–50 % MCR	1.15* nominal	1.1 * nominal
	<25 % MCR	1.7 * nominal	1.7 * nominal
Jalkanen et al. (2012)	$SFOC = SFOC_{Base} \bullet (0.455 \bullet EL^2 - 0.71 \bullet EL + 1.28)$		

Table A4
Rang of EF_{CO_2} value in different engine types and fuel types.

Engine type	Fuel type	Carbon content	$EF_{f\_CO_2}$(g/g)	$EF_{e\_CO_2}$(g/kWh)
ME	HFO/LSHFO	0.8493	3.114	545–716
ME	MGO/MDO	0.8744	3.206	529–673
AE	HFO/LSHFO	0.8493	3.114	607–716
AE	MGO/MDO	0.8744	3.206	593–721
AB	HFO/LSHFO	0.8493	3.114	950–1059
AB	MGO/MGO	0.8744	3.206	930–1026

emission inventory series reports. Despite these resources, a unified ship emission database for other regions or ports is lacking. With the increasing attention on the specific emissions of ships in different operation modes, it is recommended to create a comprehensive ship emission database to enable the timely tracking and analysis of ship emissions at various stages with the combination of new technology, data fusions of voyage report data, meteorological data, AIS data, and SP data, which would facilitate systematic studies by future researchers.

Table A5
Range of EF_{SO_2} value in different engine types and fuel types (g/kWh).

Engine type	Fuel type	Sulphur content	$EF_{f\_SO_2}$ (g/g)	$EF_{e\_SO_2}$ (g/kWh)
ME	HFO	2.43 %-2.6 %	0.0474–0.0507	8.2986–11.6697
	MDO	0.07 %-0.14 %	0.0014–0.0027	0.2254–0.5737
	LSHFO (1 %)	0.01	0.0195	3.4151–4.4884
	ECA	0.001	0.002	0.3220–0.4098
	Outside-ECA	0.005	0.0098	1.7075–2.2442
AE	HFO	2.43 %-2.6 %	0.0474–0.0507	9.2470–11.6697
	MDO	0.07 %-0.14 %	0.0014–0.0027	0.2527–0.6147
	LSHFO(1 %)	0.01	0.0195	3.8053–4.4884
	ECA	0.001	0.002	0.3610–0.4391
	Outside-ECA	0.005	0.0098	1.9027–2.2442
AB	HFO	2.43 %-2.6 %	0.0474–0.0507	14.4632–17.2509
	MDO	0.07 %-0.14 %	0.0014–0.0027	0.3961–0.8743
	LSHFO(1 %)	0.01	0.0195	5.9520–6.6350
	ECA	0.001	0.002	0.5659–0.6245
	Outside-ECA	0.005	0.0098	2.9760–3.3175

Table A6
Range of EF_{PM} value in different engine types and fuel types (g/kWh).

Engine type	Fuel type	Sulphur content	EF_{PM}	
			Method 1	Method 2
ME	HFO	2.43 %-2.6 %	1.3391–1.4006	1.2450–1.5167
	MGO	0.07 %-0.14 %	0.1738–0.2040	0.1727–0.2007
	LSHFO(1 %)	1 %	0.8218–0.9481	0.8514–0.9379
	ECA	0.001	0.1838–0.1937	0.1805–0.1875
	Outside-ECA	0.005	0.6409–0.8105	0.7137–0.7570
AE	HFO	2.43 %-2.6 %	1.3391–1.4006	1.3214–1.5167
	MGO	0.07 %-0.14 %	0.1698–0.2009	0.1749–0.2040
	LSHFO(1 %)	1 %	0.8218–0.9022	0.8828–0.9379
	ECA	0.001	0.1805–0.1893	0.1836–0.1899
	Outside-ECA	0.005	0.6409–0.7488	0.7295–0.7570
AB	HFO	2.43 %-2.6 %	1.3330–1.4249	1.7419–1.9665
	MGO	0.07 %-0.14 %	0.1444–0.1844	0.1864–0.2250
	LSHFO(1 %)	1 %	0.5692–0.6496	1.0558–1.1109
	ECA	0.001	0.1595–0.1661	0.2001–0.2048
	Outside-ECA	0.005	0.3018–0.4097	0.8160–0.8435

Table A7
Range of EF_{NO_x} value in different engine types and fuel types (g/kWh).

Keel Laid (Tier)	Engine Category		ME		AE		AB	
	ME	AE	MGO	HFO	MGO	HFO	MGO	HFO
1999 and earlier	SSD	MSD	17	18.1	13.8	14.7	2	2.1
(Tier 0)	MSD	HSD	13.2	14	10.9	11.6		
2000–2010	SSD	MSD	16	17	12.2	13		
(Tier I)	MSD	HSD	12.2	13	9.8	10.4		
2011–2015	SSD	MSD	14.4	15.3	10.5	11.2		
(Tier II)	MSD	HSD	10.5	11.2	7.7	8.2		
2016 and later	SSD	MSD	3.4	3.4–3.6	2.6	2.6–2.8		
(Tier III)	MSD	HSD	2.6	2.6–2.8	2	2–2.1		

Table A8
Range of EF_{CO} value in different engine types and fuel types (g/kWh).

Engine type	Engine category	Reference (EPA, 2020; EPA and ICF, 2009; Starcrest, 2021)	Reference (Comer et al., 2017)	Faber et al., (2020)	
				HFO	MGO
ME	SSD	1.4	0.54	0.54	0.044
	MSD	1.1	0.54	0.54	0.046
	HSD	–	–	0.54	0.54
AE	MSD	1.1	0.54	0.54	0.54
	HSD	0.9	0.54	–	–
AB	AB	0.2	0.2	0.2	0.2

Table A9
LLF value in different *EL* and pollutants.

EL	CO_2	SO_2	NO_X	*PM*	*CO*
<=2%	1	1	4.63	7.29	9.68
3 %	1	1	2.92	4.33	6.46
4 %	1	1	2.21	3.09	4.86
5 %	1	1	1.83	2.44	3.89
6 %	1	1	1.6	2.04	3.25
7 %	1	1	1.45	1.79	2.79
8 %	1	1	1.35	1.61	2.45
9 %	1	1	1.27	1.48	2.18
10 %	1	1	1.22	1.38	1.96
11 %	1	1	1.17	1.3	1.79
12 %	1	1	1.14	1.24	1.64
13 %	1	1	1.11	1.19	1.52
14 %	1	1	1.08	1.15	1.41
15 %	1	1	1.06	1.11	1.32
16 %	1	1	1.05	1.08	1.24
17 %	1	1	1.03	1.06	1.17
18 %	1	1	1.02	1.04	1.11
19 %	1	1	1.01	1.02	1.05
>=20 %	1	1	1	1	1

Table A10
Information of vessels during SP connections.

Vessel ID	Duration (hour)	EO_{SP_AE}(kWh)	L_{AE}(kW)
Ship 1	6	13,200	2200
Ship 2	5	4852	970
Ship 3	17	19,652	1156
Ship 4	5	6019	1204
Ship 5	8	9081	1135
Ship 6	5	6653	1331
Ship 7	6	8175	1363
Ship 8	12	10,345	862
Ship 9	1.2	1320	1100
Ship 10	4.4	7128	1620
Ship 11	2.3	2790	1213
Ship 12	2	2150	1075
Ship 13	2.3	2070	900

4.4.2. Strict regulations on carbon and NO_X emissions

As initiatives for carbon neutrality and carbon peaking gain momentum, ship carbon emissions are expected to receive increased attention. Meanwhile, the issue of NO_X emissions is likely to face increased restrictions, encouraging the broad adoption and implementation of measures to reduce both carbon and nitrogen emissions. The application of SP, the methodologies, and the renewable energy resources may pave the way for future research trends in ship carbon and nitrogen reduction.

4.4.3. Expanded application of SP

Taking into account the diversity of ship sizes and types, it is suggested to conduct further analyses on specific ship types, such as cruises, bulk carriers, and tankers. Furthermore, it is crucial for future studies to more closely examine the effects of SP-related policies and regulations, as well as the implications of SP's growing adoption in forthcoming years, on the operational efficiency and effectiveness of ports, with a special emphasis on the quality of port electrical systems.

5. Conclusion

Grounded in the advancement of SP promotion and application, this paper critically establishes a scheme for SP data to enhance emission estimation of berthed containerships. Structured as a six-step process, this study begins with an extensive literature review to identify the state-of-the-art and research gaps in the existing methods of estimating ship-at-berth emissions. Second, ship-at-berth emissions from AEs are improved by applying SP data after demonstrating its reliability. Third, a new holistic approach is introduced to incorporate AEs, ABs, and low-load MEs, along with suggested fuel-related parameters and real SP data, to improve the accuracy of emission estimations. It is then followed by case studies, including a single containership and multiple containerships, to demonstrate the reliability of SP data-based methods over traditional AEs estimation techniques. Based on the average estimations derived from multiple containerships using HFO, a comparative analysis is conducted to demonstrate the performance of the proposed method and to investigate the effects of prominent emission reduction measures. Finally, the implications and future research

Table A11
Static characteristics of Investigated containerships.

Ship ID	Year of Build	Keel Laid	GT	DWT	NT	TEU	ref C	ME MCR	RPM	Max. Speed	Service Speed	S&C	Stroke	AE No.	MCR	AB No.
Ship 1	2018	2015.12	194,864	202,133	115,302	20,038	1,000	55,000	72	22	19	22&168	2	4	3360*2 + 4500*2	3
Ship 2	2008	2008.3	114,394	110,038	54,951	10,060	800	68,640	94	25.8	24.8	24&250	2	4	3500	1
Ship 3	2008	2007.1	114,394	109,950	54,951	10,060	800	68,640	94	25.8	24.8	24&250	2	4	3500	1
Ship 4	2014	2013.9	99,995	103,668	48,182	9,466	942	56,070	97	25.7	24.5	24.7&210	2	4	3300	N/A
Ship 5	2013	2012.12	101,063	103,891	49,583	8,508	948	56,070	97	25.7	24.5	24.7&210	2	4	3500	1
Ship 6	2014	2013.1	99,995	103,668	48,182	9,466	942	56,070	97	26.1	24.5	24.7&210	2	4	3300	N/A
Ship 7	2013	2012.9	99,995	103,668	48,182	8,452	942	56,070	97	25.7	24.5	24.7&210	2	4	3300	N/A
Ship 8	2014	2013.5	101,063	104,397	49,583	8,508	948	56,070	97	25.7	24.5	224.7&210	2	4	3300	N/A
Ship 9	2013	2013.8	99,995	104,262	48,182	8,452	942	56,070	97	25.9	24.5	24.7&210	2	4	3300	N/A
Ship 10	2013	2013.2	99,995	103,668	48,236	8,452	942	56,070	97	25.7	24.5	24.7&210	2	4	3300	N/A
Ship 11	2019	2015.7	150,754	146,749	68,520	14,220	1,000	48,900	76	N/A	24	23&168.5	2	4	3650	1
Ship 12	2015	2014.12	144,651	145,368	66,967	14,080	1000	52,723	79	24.7	23.2	23&175	2	4	2950*2 + 3900*2	1
Ship 13	2018	2015.9	151,451	146,749	68,253	14,220	1000	48,900	76	N/A	23	23&168.5	2	4	3650	N/A

Table A12
Descriptive statistics of results in multiple containerships.

Vessel ID	P_{AE} Average	CV	L_{AE} Average	CV	FC_{AE} Average	CV	SO_X Average	CV	CO_2 Average	CV	NO_X Average	CV	PM Average	CV	CO Average	CV
Ship 1	20,462	1.92	5869	1.41	12,625	2.38	290	2.27	47,139	2.16	830	2.38	41	2.04	176	2.73
Ship 2	12,451	1.11	3929	0.91	4903	1.08	104	1.74	18,070	1.03	300	1.12	19	2.06	79	2.92
Ship 3	12,410	1.11	3889	0.89	16,669	1.08	353	1.74	60,913	1.03	1018	1.13	66	2.06	269	2.92
Ship 4	10,969	1.04	3515	0.84	4278	0.93	89	1.67	15,309	0.91	256	0.98	17	1.96	69	2.92
Ship 5	10,883	1.01	3512	0.84	6859	0.94	141	1.64	24,583	0.92	410	0.99	26	1.96	111	2.94
Ship 6	10,969	1.04	3515	0.84	4278	0.93	89	1.67	15,309	0.91	256	0.98	17	1.96	69	2.92
Ship 7	10,760	1.01	3471	0.84	5074	0.93	104	1.64	18,160	0.91	303	0.97	19	1.97	82	2.94
Ship 8	10,820	1.02	3486	0.84	10,230	0.94	210	1.65	36,629	0.92	611	0.99	39	1.97	166	2.94
Ship 9	10,769	1.01	3473	0.84	1015	0.93	21	1.64	3634	0.91	61	0.97	4	1.97	16	2.94
Ship 10	10,760	1.01	3471	0.84	3721	0.93	76	1.64	13,318	0.91	222	0.97	14	1.97	60	2.94
Ship 11	14,727	1.58	4458	1.15	2969	1.72	68	2.06	11,032	1.57	189	1.76	10	1.87	47	2.91
Ship 12	14,428	1.52	4374	1.11	2510	1.6	57	2.04	9293	1.47	159	1.65	9	1.89	40	2.9
Ship 13	14,760	1.58	4465	1.15	3096	1.73	71	2.06	11,505	1.58	197	1.77	11	1.87	49	2.91
Average	12,705	1.23	3956	0.96	6017	1.24	129	1.80	21,915	1.17	370	1.28	22	1.97	95	2.91

directions for both practical and academic areas are outlined. Hence, the findings of this study contribute new approaches and insights to scientifically and reasonably refining ship-at-berth emission estimates. More specifically,

(1) The estimation of ship emissions at berth is a complex process influenced by various factors, including ship size, engine type, engine category, fuel type, berthing time, and emission reduction measures.

(2) Estimates from FC methods are generally higher than those from EO ones, with both typically exceeding actual emissions, highlighting the importance of utilising SP data to research vessel characteristics and enhance the accuracy of emission estimation during berthing mode.

(3) CO_2 and SO_2 emissions from ABs during berthing, though slightly lower than from AEs, are major sources of emissions. Additionally, emissions like CO, $NO_{X,}$ and PM from MEs during berthing should not be overlooked due to their sensitivity to ME's low load.

(4) Following the establishment of ECAs and the 2020 regulations, there has been a significant decrease in SO_2 and PM emissions while CO_2 emissions have yet shown a significant reduction. In some cases, an increase instead happens due to the increased fuel oil consumption driven by fuel compliance requirements.

(5) Among various emission reduction measures, the combined use of SP and alternative fuels during ship berthing has shown to be preferred in significantly reducing pollutant emissions, presenting a promising avenue for environmental impact mitigation.

The findings demonstrate that SP is an effective measure for reducing various pollutants from those ships at berth. This implies that governments could initially promote SP through incentives for its installation and operation, and subsequently implement regulations for specific routes and ship types to show strong feasibility and economic benefits, thereby reducing ship-at-berth emissions (Gong et al., 2024). Moreover, integrating multi-emission reduction measures with SP, such as alternative fuels and restructuring the SP supply ecosystem, could achieve zero emissions. SP also has the potential to improve energy management for both port and shipboard systems, paving the way for efficient and sustainable maritime operations. Additionally, great emphasis should be placed on the collection and timely public release of SP data, which may provide new opportunities for further research.

The proposed method in this paper employs SP data, vessel characteristics, and LA series reports on emission inventory to estimate ship-at-berth emissions with a limited sample. However, its applicability to a broader fleet can be feasible after appropriate further validation and potential adaptation are undertaken. A significant limitation of this study is the restricted accessibility of public SP data. Additionally, methods and parameters used for estimating emissions from ABs and low-load MEs are based on the literature. Despite these limitations, the comparative analysis conducted on single-containership and multi-containership models successfully meet the research objectives.

CRediT authorship contribution statement

Jinggai Wang: Writing – review & editing, Writing – original draft, Validation, Software, Methodology, Investigation, Data curation, Conceptualization. **Huanhuan Li:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Project administration, Methodology, Formal analysis, Conceptualization, Resources. **Zaili Yang:** Writing – review & editing, Visualization, Validation, Supervision, Investigation, Funding acquisition, Formal analysis, Project administration. **Ying-En Ge:** Writing – original draft, Supervision, Resources, Project administration, Investigation, Funding acquisition, Conceptualization, Validation, Writing – review & editing.

Data availability

Data will be made available on request.

Acknowledgements

This work is supported by the National Natural Science Foundation of China (Grant No. 72031005 and 72361137003), the Fundamental Research Funds for the Central Universities, CHD (Grant: 300102344301), European Research Council project under the European Union's Horizon 2020 research and innovation program (TRUST CoG 2019 864724), the China Scholarship Council (File No. 202308310306), and Shanghai Maritime University (File No. 2023YBR009).

Appendix

Table A1, Table A2, Table A3, Table A4, Table A5, Table A6, Table A7, Table A8, Table A9, Table A10, Table A11, Table A12).

References

Adamo, F., Andria, G., Cavone, G., De Capua, C., Lanzolla, A.M.L., Morello, R., Spadavecchia, M., 2014. Estimation of ship emissions in the port of Taranto. Measurement 47, 982–988. https://doi.org/10.1016/j.measurement.2013.09.012.

Chen, S.K., Meng, Q., Jia, P., Kuang, H.B., 2021. An operational-mode-based method for estimating ship emissions in port waters. Transport. Res. Part D-Transport. Environ. 101, 15. https://doi.org/10.1016/j.trd.2021.103080.

China Shipowners' Association. 2019. World's First Successful Shore Power Connection Achieved by a 20,000 TEU Ultra-Large Container Ship. China Shipowners' Association. Available: http://www.csoa.cn/doc/14667.jsp [Accessed January 9 2019].

Comer, B., Olmer, N., Mao, X., Roy, B. & Rutherford, D. 2017. Black carbon emissions and fuel use in global shipping 2015. International Council on Clean Transportation: International Council on Clean Transportation. Available: https://theicct.org/publication/black-carbon-emissions-and-fuel-use-in-global-shipping-2015/ [Accessed December 15 2017].

Cooper, D. & Gustafsson, T. 2004a. Methodology for calculating emissions from ships: 1. Update of emission factors. IVL Swedish Environmental Research Institute: Swedish Environmental Protection Agency. Available: https://urn.kb.se/resolve?urn=urn:nbn:se:naturvardsverket:diva-7084 [Accessed June 28 2017].

Cooper, D. & Gustafsson, T. 2004b. Methodology for calculating emissions from ships: 2. Emission factors for 2004 reporting. IVL Swedish Environmental Research Institute: Swedish Environmental Protection Agency. Available: https://urn.kb.se/resolve?urn=urn:nbn:se:naturvardsverket:diva-7083 [Accessed June 28 2017].

Corbett, J.J., Fischbeck, P., 1997. Emissions from ships. Science 278, 823–824. https://doi.org/10.1126/science.278.5339.823.

Corbett, J.J., Koehler, H.W., 2003. Updated emissions from ocean shipping. J. Geophys. Res-Atmos 108. https://doi.org/10.1029/2003JD003751.

Dai, L., Hu, H., Wang, Z.J., Shi, Y.F., Ding, W.Y., 2019. An environmental and techno-economic analysis of shore side electricity. Transport. Res. Part D-Transport. Environ. 75, 223–235. https://doi.org/10.1016/j.trd.2019.09.002.

Daniel, H., Antunes, C.H., Trovao, J.P.F., Williams, D., 2023. Shore operations enhancement of bulk carriers based on a multi-objective sizing approach. Energ. Convers. Manage. 276, 19. https://doi.org/10.1016/j.enconman.2022.116497.

Daniel, H., Trovão, J. P. F. & Williams, D. 2021. Shore power as a first step toward shipping decarbonization and related policy impact on a dry bulk cargo carrier. eTransportation, 11. 100150. Doi: 10.1016/j.etran.2021.100150.

Epa. 2020. Ports Emissions Inventory Guidance: Methodologies for Estimating Port-Related and Goods Movement Mobile Source Emissions. United States Environmental Protection Agency: United States Environmental Protection Agency Ann Arbor, MI, USA. Available: https://www.epa.gov/sites/default/files/2020-10/documents/ports-emissions-inventory-guidance-webinar-2020-10-29.pdf [Accessed October 29 2020].

Faber, S., Hanayama, S., Zhang, S., Pereda, P., Comer, B., Hauerhof, E. & Kosaka, H. 2020. Fourth IMO GHG Study 2020. International Maritime Organization: International Maritime Organization. Available: https://www.imo.org/en/ourwork/Environment/Pages/Fourth-IMO-Greenhouse-Gas-Study-2020.aspx [Accessed March 23 2021].

Gligor, D.M., Davis-Sramek, B., Tan, A., Vitale, A., Russo, I., Golgeci, I., Wan, X., 2021. Utilizing blockchain technology for supply chain transparency: A resource orchestration perspective. J. Bus. Logist. 43, 20. https://doi.org/10.1111/jbl.12287.

Gong, Y., Zhou, Y., Liu, X., Huang, Y., Lu, Q., 2024. Identifying effective incentive policies for promoting widespread adoption of shore power technology. Transport. Res. Part D-Transport. Environ. 126 https://doi.org/10.1016/j.trd.2023.103998.

Gutierrez-Romero, J.E., Esteve-Perez, J., Zamora, B., 2019. Implementing Onshore Power Supply from renewable energy sources for requirements of ships at berth. Applied Energy 255. https://doi.org/10.1016/j.apenergy.2019.113883.

He, Z.X., Lam, J.S.L., Liang, M., 2023. Impact of Disruption on Ship Emissions in Port: Case of Pandemic in Long Beach. Sustainability-Basel 15, 16. https://doi.org/10.3390/su15097215.

Hickman, J., Hassel, D., Joumard, R., Samaras, Z., Sorenson, S., 1999. Methodology for calculating transport emissions and energy consumption [Accessed] European Commission. Available. https://trimis.ec.europa.eu/system/files/project/documents/meet.pdf.

Epa & Icf. 2009. Current methodologies in preparing mobile source port-related emission inventories. U.S. Environmental Protection Agency: ICF International. Available: https://www.epa.gov/sites/default/files/2016-06/documents/2009-port-inventory-guidance.pdf [Accessed April 2009].

Imo. 2021. Fourth IMO Greenhouse Gas Study 2020. International Maritime Organization: International Maritime Organization. Available: https://wwwcdn.imo.org/localresources/en/OurWork/Environment/Documents/Fourth%20IMO%20GHG%20Study%202020%20-%20Full%20report%20and%20annexes.pdf [Accessed 08 August 2020].

Jalkanen, J.P., Brink, A., Kalli, J., Pettersson, H., Kukkonen, J., Stipa, T., 2009. A modelling system for the exhaust emissions of marine traffic and its application in the Baltic Sea area. Atmos. Chem. Phys. 9, 9209–9223. https://doi.org/10.5194/acp-9-9209-2009.

Jalkanen, J.P., Johansson, L., Kukkonen, J., Brink, A., Kalli, J., Stipa, T., 2012. Extension of an assessment model of ship traffic exhaust emissions for particulate matter and carbon monoxide. Atmos. Chem. Phys. 12, 2641–2659. https://doi.org/10.5194/acp-12-2641-2012.

Jian, G., Wei, W., Yi-Qiang, P., Xiao-Jing, W., Xue-Jun, F., Yan, Z., 2017. Study on vessel emission inventory based on STEAM. Journal of Safety and Environment 1963–1968. https://doi.org/10.13637/j.issn.1009-6094.2017.05.066.

Kotrikla, A.M., Lilas, T., Nikitakos, N., 2017. Abatement of air pollution at an aegean island port utilizing shore side electricity and renewable energy. Mar. Pol. 75, 238–248. https://doi.org/10.1016/j.marpol.2016.01.026.

Lee, H., Park, D., Choo, S., Pham, H.T., 2020. Estimation of the Non-Greenhouse Gas Emissions Inventory from Ships in the Port of Incheon. Sustainability-Basel 12, 18. https://doi.org/10.3390/su12198231.

Lee, H., Pham, H.T., Chen, M.W., Choo, S., 2021. Bottom-Up Approach Ship Emission Inventory in Port of Incheon Based on VTS Data. J. Adv. Transp. 2021, 1–16. https://doi.org/10.1155/2021/5568777.

Li, Z.H., He, L., 2011. Research on Emission Methods for Estimating Ship Pollutant Emission Inventory. Guangxi Journal of Light Industry 5, 79–80. https://doi.org/10.3969/j.issn.1003-2673.2011.05.039.

Liu, H., Shang, Y., Shang, X.X., Fu, M.L., 2018. Review of methods and progress on shipping emission inventory studies. Acta Scientiae Cricumstantiae 38, 1–12. https://doi.org/10.13671/j.hjkxxb.2017.0257.

Lopez-Aparicio, S., Tonnesen, D., Thanh, T.N., Neilson, H., 2017. Shipping emissions in a Nordic port: Assessment of mitigation strategies. Transport. Res. Part D-Transport. Environ. 53, 205–216. https://doi.org/10.1016/j.trd.2017.04.021.

Lu, H.Y., Huang, L.F., 2021. Optimization of Shore Power Deployment in Green Ports Considering Government Subsidies. Sustainability-Basel 13. https://doi.org/10.3390/su13041640.

Nguyen, P.N., Woo, S.H., Kim, H., 2022. Ship emissions in hotelling phase and loading/unloading in Southeast Asia ports. Transport. Res. Part D-Transport. Environ. 105, 13. https://doi.org/10.1016/j.trd.2022.103223.

Peng, X., Ding, Y., Yi, W., Laroussi, I., He, T., He, K., Liu, H., 2024a. The inland waterway ship emission inventory modeling: The Yangtze River case. Transport. Res. Part D-Transport. Environ. 129 https://doi.org/10.1016/j.trd.2024.104138.

Peng, X., Ding, Y.X., Yi, W., Laroussi, I., He, T.K., He, K.B., Liu, H., 2024b. The inland waterway ship emission inventory modeling: The Yangtze River case. Transport. Res. Part D-Transport. Environ. 129, 13. https://doi.org/10.1016/j.trd.2024.104138.

Port of Los Angeles. 2024. Annual Inventory of Air Emissions. Available: https://www.portoflosangeles.org/environment/air-quality/air-emissions-inventory [Accessed].

Poulsen, R.T., Ponte, S., Sornn-Friese, H., 2018. Environmental upgrading in global value chains: The potential and limitations of ports in the greening of maritime transport. Geoforum 89, 83–95. https://doi.org/10.1016/j.geoforum.2018.01.011.

Sciberras, E.A., Zahawi, B., Atkinson, D.J., Juando, A., Sarasquete, A., 2016. Cold ironing and onshore generation for airborne emission reductions in ports. Proc. Inst. Mech. Eng. Part M- J. Eng. Marit. Environ. 230, 67–82. https://doi.org/10.1177/1475090214532.

Shu, Y.Q., Hu, A.Y., Zheng, Y.Z., Gan, L.X., Xiao, G.N., Zhou, C.H., Song, L., 2023. Evaluation of ship emission intensity and the inaccuracy of exhaust emission estimation model. Ocean Eng. 287, 11. https://doi.org/10.1016/j.oceaneng.2023.115723.

Singh, S., Dwivedi, A., Pratap, S., 2023. Sustainable Maritime Freight Transportation: Current Status and Future Directions. Sustainability-Basel 15, 23. https://doi.org/10.3390/su15086996.

Smith, T., Jalkanen, J., Anderson, B., Corbett, J., Faber, J., Hanayama, S., O'keeffe, E., Parker, S., Johansson, L. & Aldous, L. 2015. Third IMO greenhouse gas study 2014. International Maritime Organization: International Maritime Organization. Available: https://wwwcdn.imo.org/localresources/en/OurWork/Environment/Documents/Third%20Greenhouse%20Gas%20Study/GHG3%20Executive%20Summary%20and%20Report.pdf [Accessed January 1 2015].

Starcrest. 2005. Port of Los Angeles Baseline Air Emissions Inventory CY 2001. Port of Los Angeles: Starcrest Consulting Group, LLC. Available: https://kentico.portoflosangeles.org/getmedia/e9147367-eac0-4cc3-add7-6bfb6123f7e0/REPORT_Final_BAEI [Accessed July 2005].

Starcrest. 2007. Port of Los Angeles Inventory of a Air Emissions CY 2005. Port of Los Angeles: Starcrest Consulting Group, LLC. Available: https://kentico.portoflosangeles.org/getmedia/59baf614-fdfe-4cfa-9d58-3032d32583d7/2005_Air_Emissions_Inventory_Full_Doc [Accessed September 2007].

Starcrest. 2008. Port of Los Angeles Inventory of a Air Emissions CY 2007. Port of Los Angeles: Starcrest Consulting Group, LLC. Available: https://kentico.portoflosangeles.org/getmedia/828afe97-0f6d-482b-88bd-e89793597ed1/2007_Air_Emissions_Inventory [Accessed December 2008].

Starcrest. 2011. Port of Los Angeles Inventory of Air Emissions CY 2010. Port of Los Angeles: Starcrest Consulting Group, LLC. Available: https://kentico.portoflosangeles.org/getmedia/26d2bb85-c08c-4776-afce-40677296e048/2010_Air_Emissions_Inventory [Accessed July 2011].

Starcrest. 2021. San Pedro Bay Ports Emissions Inventory Methodology Report. Port of Los Angeles: Starcrest Consulting Group, LLC. Available: https://kentico.portoflosangeles.org/getmedia/5cf9340c-869f-47f2-afab-710b39355070/2020_SPBP_Emissions_Inventory_Methodology_v2 [Accessed September 2021].

Starcrest. 2023. Port of Los Angeles Inventory of Air Emissions CY 2022. Port of Los Angeles: Starcrest Consulting Group, LLC. Available: https://kentico.portoflosangeles.org/getmedia/409590b5-0e6a-4c15-8d9b-fcdb02624933/2022_Air_Emissions_Inventory [Accessed August 2023].

Stolz, B., Held, M., Georges, G., Boulouchos, K., 2021. The CO2 reduction potential of shore-side electricity in Europe. Applied Energy 285, 14. https://doi.org/10.1016/j.apenergy.2020.116425.

Styhre, L., Winnes, H., Black, J., Lee, J., Le-Griffin, H., 2017. Greenhouse gas emissions from ships in ports - Case studies in four continents. Transport. Res. Part D-Transport. Environ. 54, 212–224. https://doi.org/10.1016/j.trd.2017.04.033.

Tichavska, M., Tovar, B., Gritsenko, D., Johansson, L., Jalkanen, J.P., 2019. Air emissions from ships in port: Does regulation make a difference? Transp. Policy 75, 128–140. https://doi.org/10.1016/j.tranpol.2017.03.003.

Trozzi, C. & Vaccaro, R. 2006. Methodologies for estimating air pollutant emissions from ships: a 2006 update. *Poster presented at 2nd Environment & Transport Conference (including 15th Transport and Air Pollution conference)*. Reims, France.

United Nations. 2018. Review of Maritime Transport 2018. UN trade & development: UNCTAD. Available: https://unctad.org/publication/review-maritime-transport-2018 [Accessed October 3 2018].

Wang, T.S., Cheng, P.Y., Zhen, L., 2023b. Green development of the maritime industry: Overview, perspectives, and future research opportunities. Transp. Res. Pt. e-Logist. Transp. Rev. 179, 21. https://doi.org/10.1016/j.tre.2023.103322.

Wang, C.F., Corbett, J.J., Firestone, J., 2007a. Modeling energy use and emissions from North American shipping: Application of the ship traffic, energy, and environment model. Environ. Sci. Technol. 41, 3226–3232. https://doi.org/10.1021/es060752e.

Wang, C.F., Corbett, J.J., Winebrake, J.J., 2007b. Cost-effectiveness of reducing sulfur emissions from ships. Environ. Sci. Technol. 41, 8233–8239. https://doi.org/10.1021/es070812w.

Wang, J.G., Zhong, M.S., Wang, T.N., Ge, Y.E., 2023a. Identifying industry-related opinions on shore power from a survey in China. Transp. Policy 134, 65–81. https://doi.org/10.1016/j.tranpol.2023.02.010.

Wang, J.G., Li, H.H., Yang, Z.L., Ge, Y.E., 2024. Shore power for reduction of shipping emission in port: A bibliometric analysis. Transp. Res. Pt. e-Logist. Transp. Rev. 188 https://doi.org/10.1016/j.tre.2024.103639.

Yang, J.H., 2021. A Study on the Reasonable Choice and Utilization of Incoterms 2020 Rules from the Perspective of Logistics and Supply Chain Management. J. Korea. Trade. 25, 152–168. https://doi.org/10.35611/jkt.2021.25.1.152.

Yang, L., Zhang, Q.J., Zhang, Y.J., Lv, Z.Y., Wang, Y.A., Wu, L., Feng, X., Mao, H.J., 2021. An AIS-based emission inventory and the impact on air quality in Tianjin port based on localized emission factors. Sci. Total Environ. 783, 11. https://doi.org/10.1016/j.scitotenv.2021.146869.

Yu, J., Voß, S., Tang, G., 2019. Strategy development for retrofitting ships for implementing shore side electricity. Transport. Res. Part D-Transport. Environ. 74, 201–213. https://doi.org/10.1016/j.trd.2019.08.004.

Zis, T.P.V., 2019. Prospects of cold ironing as an emissions reduction option. Transp. Res. Pt. A-Policy Pract. 119, 82–95. https://doi.org/10.1016/j.tra.2018.11.003.

Zis, T., North, R.J., Angeloudis, P., Ochieng, W.Y., Bell, M.G.H., 2014. Evaluation of cold ironing and speed reduction policies to reduce ship emissions near and at ports. Marit. Econ. Logist. 16, 371–398. https://doi.org/10.1057/mel.2014.6.