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CAN AI ADDRESS THE SHORTCOMINGS OF THE CURRENT PORT EMISSIONS INVENTORY PRACTICES?

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1. **ABSTRACT:** The creation of air emission inventories (EIs) in seaports has proven to be a valuable method providing a quantitative basis to meet increasingly stringent regulations and ambitious emission reduction targets. These inventories are essential for implementing and monitoring necessary measures. However, despite their significance, EIs are often unpublished or not regularly updated, obscuring the ports' contributions to emissions. Key reasons for this include data security issues, accuracy problems, and the substantial effort required to obtain and analyze the necessary emission data. Recent advancements in artificial intelligence (AI) offer promising solutions to reduce this effort and enhance the accuracy of these inventories. Based on a systematic literature review of 13 relevant articles, this study examines the potentials and barriers of AI and machine learning (ML) techniques. The findings reveal the AI/ML techniques considered in the context of EIs, pinpoint the barriers that can be overcome using AI/ML, and highlight the improvements needed for the further application of these technologies. The proposed future research agenda aims to incorporate practical evidence from port authorities, providing a comprehensive understanding of how AI can be effectively leveraged for improving the accuracy and relevance of emission inventories.

2. INTRODUCTION

Seaports are crucial hubs for global trade, facilitating activities such as transport, terminal operations, and warehousing. However, these operations have a significant negative impact on both the climate and the local environment, primarily due to the consistent use of fossil fuels [2.]. As the number of containers handled in the world's largest seaports continues to rise, driven by the growing volume of global trade [1.] (see Figure 1), and the global shipping fleet remains heavily dependent on conventional fossil fuels [3.] (see Figure 2), pollutant emissions are expected to remain significant. The 10 largest container ports alone threaten to exacerbate climate change and have a direct negative impact on the health of around 80 million people [4.].

Following increased public awareness as well as ever-stricter regulations on global climate changes, such as those by the EU and the International Maritime Organisation (IMO), seaports face mounting pressure to meet global climate targets while minimizing adverse local environmental impacts [5.]. Among the primary concerns for seaports, such as climate change or energy efficiency, air quality has been a top priority since 2013 [6.]. In order to improve air quality and find suitable strategies to reduce air pollution in and around seaports, it is essential to determine the causes, timing, and locations of

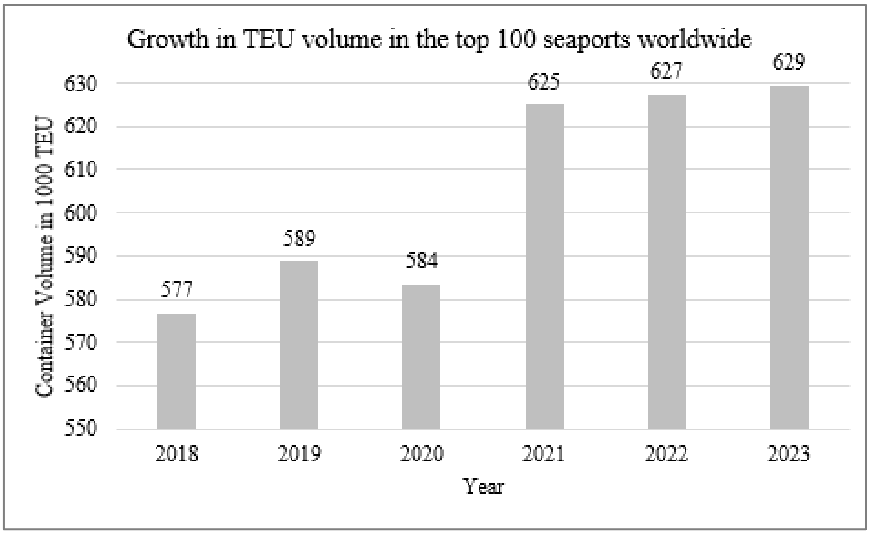

Figure 1. Growth in TEU volume in the top 100 seaports worldwide between 2018 and 2023. Source: [1.]

emissions. This is achieved by compiling emission inventories (EIs). According to IMO and IAPH [7.], emissions inventories (EIs) document the various sources of port-related emissions and their associated activities. These activities are then converted into energy consumption data and then into emissions

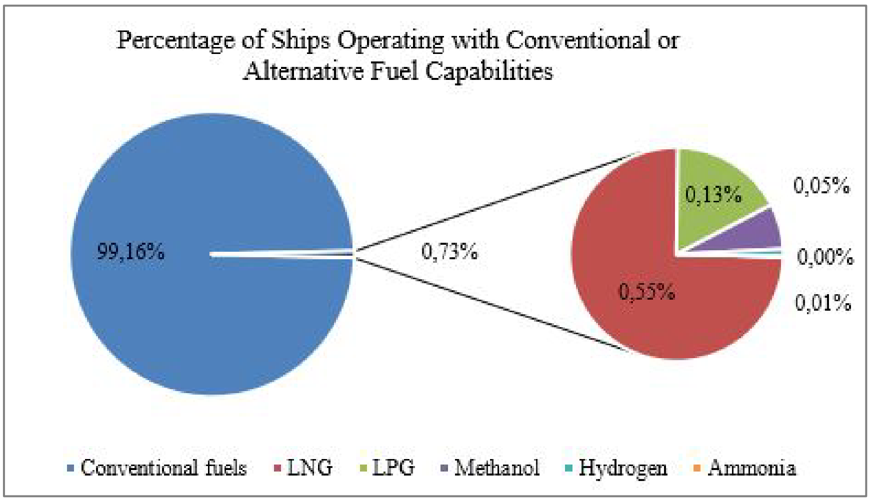

Figure 2. Only 0.73% of all ships are currently capable of operating on alternative fuels, which remains a minor fraction compared to the 99.16% using conventional fossil fuels. Source: [3.]

figures. EIs provide insights into the activities and related emissions of different sources within specific geographic, operational, and temporal contexts.

In response to public concerns, the Port of Los Angeles [8.] and Long Beach [9.] initiated the first seaport-based air emission inventory (EI) in 2005. Since then, these two ports have reported the latest results on the climate gas CO_2 and air pollutants nitrogen oxides (NO_x), sulphur oxides (SO_x), particulate matter (PM), carbon monoxide (CO), etc. from sources such as shipping, rail transport, on-road and offroad traffic (cargo-handling equipment). The development of these pollutants over a ten-year period shows that emission reduction strategies like ECAs and mandatory use of scrubbers noticeably impacted air pollution control in and around seaports.

Van Aardenne [10.] examined in his thesis concerns regarding the reliability and accuracy of EIs, which determine their usefulness. These concerns date back to the 1990s and stem from the practical challenge of measuring emissions at every individual source, necessitating the use of emission factors for quantification. This approach, however, leads to issues such as the quality of input data and the reliance on incomplete information, often substituted by simplifications or approximations.

These data-related issues remain relevant today. Cammin *et al.* [11.] investigated the potential for automating EIs and identified several challenges. These include the traditional manual work, which, on one hand, slows down the process and, on the other hand, causes data quality issues through questionnaire files to fill out. Additionally, the handling of port tenant confidential data and the existence of weak holistic information systems were highlighted as significant obstacles. Cammin *et al.* [12.] also noted that a common approach is to use assumptions to fill in gaps where data is missing, such as fuel consumption. Furthermore, additional problems stem from these issues. Sustainability reports, which often serve as one-way communication channels and partially report emissions, frequently distort facts to enhance their public image, which can result in the dissemination of misleading information, a practice commonly referred to as "greenwashing. [13., 14.]. Accurate emission inventories (EIs) are essential for monitoring emissions, developing sustainability strategies, and ensuring regulatory compliance [15.]. However, traditional methods of creating EIs in seaports face several challenges, including data collection difficulties, high costs, and the need for continuous monitoring. These issues often result in incomplete or imprecise EIs, undermining efforts to mitigate environmental impacts. Especially, one of the most significant barriers to reducing emissions is the high cost associated with the investment, operation, and maintenance of various technical, operational, or managerial emission reduction measures [16., 17.]. The need to invest in beneficial but non-mandatory EIs further intensifies these challenges.

As Durlik *et al.* [18.] highlight, artificial intelligence (AI) and machine learning (ML) are gaining increasing attention within the scientific community, recognized also for their potential to enhance maritime sustainability. One of the most promising benefits is their capability to facilitate real-time decision-making, thanks to the growing reliability of predictive models [19.]. AI is a field of computer science that involves creating systems capable of performing tasks that require human-like intelligence, such as reasoning, learning, and problem-solving. ML is a subset of artificial intelligence. Its primary goal is to develop systems that can learn autonomously, without human intervention. These systems improve by utilizing existing data, pre-existing knowledge, and new information gained through experiences and interactions. [20.] ML algorithms can be either supervised or unsupervised, or a combination of both [21.].

In *supervised* learning, the model is trained on labeled data, meaning the training dataset includes both input data and corresponding output labels [22.]. The primary goal is to learn a mapping from inputs to outputs, allowing the model to make predictions or classify data based on these input-output pairs. Common techniques include linear regression (LR), support vector machine (SVM), decision tree (DT), random forest (RF), neural network (NN), and k-nearest neighbour (KNN).

In *unsupervised* learning, the model is trained on unlabeled data, where the training dataset contains only input data without any corresponding output labels [23.]. The main objective is to identify patterns or structures within the data, with the uncovering of hidden relationships or clusters. Common techniques encompass k-means clustering, hierarchical clustering, and principal component analysis (PCA).

While the application of AI and ML techniques for various sustainability topics in maritime studies is on the rise, their specific use in managing emission inventories in seaports remains largely unexplored. Therefore, this review aims to explore the intersection of artificial intelligence (AI) and air emission inventories in the maritime industry, with a focus on shipping and port operations. The primary objective is to highlight how AI technologies can address the existing challenges and leverage opportunities to improve air quality in related operations. Specifically, this review answers the following research questions (RQ):

RQ1: What AI/ML techniques are considered by the selected literature?

Answering the RQ1 would allow researchers to identify and distinguish the relevance of AI/ML techniques in the scientific approaches and discussion towards EIs.

RQ2: Which barriers can be removed by using AI/ML techniques?

Answering the RQ2 would bring an understanding of the advantages of AI/ML techniques and thus guidance for further implementation.

RQ3: What improvements are required for the further use of ML/AI techniques?

Answering the RQ3 would enable researchers to identify future directions.

The rest of the paper is structured as follows. Section 2.2 presents practical applications of AI/ML techniques in leading seaports. Section 3 provides details on the methodology. Section 4 outlines the results and discusses them in relation to the research questions. Finally, Section 5 summarizes the results, presents critical reflections, and proposes directions for future research.

2.2 Current AI practices in selected seaports

Despite several challenges hindering the widespread adoption, AI is rapidly emerging as a key focus in the maritime industry. Leading seaports are making significant progress in using advanced AI solutions to tackle a range of challenges, including those related to sustainability.

Durlik *et al.* [19.] discuss how the Port of *Rotterdam* has implemented AI-driven solutions to optimize port logistics, improve fuel efficiency, and reduce emissions. By integrating AI with Internet of Things (IoT) sensors, the port is able to gather real-time data and optimize port operations, including vessel arrival scheduling and cargo handling. The integration of AI also helps predict emissions, allowing the port to implement mitigation strategies proactively. The Port of *Antwerp* uses AI to power its digital twin, a real-time digital replica of the port area, providing detailed insights such as ship locations, equipment status, and energy production, with the Advanced Port Information & Control Assistant (APICA) serving as the intelligent core of the system. [24.] Germany's Port of *Hamburg* (HHLA) is among the pioneering ports globally to develop machine learning (ML) solutions for its Hamburg container terminals, aiming to predict container dwell times at the terminal. [25.] Liu *et al.* [26.] highlight the Port of *Los Angeles*'s innovative use of AI to address air pollution and enhance emissions monitoring. The port employs real-time air quality monitoring systems, leveraging machine learning and satellite imagery, to gain detailed insights into emissions from various sources, including ships, trucks, and cranes. This shift to real-time data enables quicker responses and more accurate emissions inventories. The Maritime and Port Authority of *Singapore* (MPA) intends to implement AI and digital twins to optimize vessel route planning. This initiative aims to improve safety and minimize emissions in maritime operations. The objective is to achieve just-in-time arrivals, thereby reducing vessel turnaround times in port. [27.] The Port of *Valencia* in Spain has developed AI solutions aimed at reducing its environmental impact. By using AI for predictive maintenance, energy optimization, and automated vessel scheduling, the port has made strides in reducing operational inefficiencies and lowering emissions. [28.]

3. METHODOLOGY

The aim of this study is to systematically gather and analyze information on the application of AI/ML techniques in seaport emission inventories (EIs). To achieve this, a systematic literature review was conducted. The literature search was carried out in scientific databases of Web of Science and Scopus, using the following terms, their combinations, and their singular/plural forms in titles or abstracts:

- Terms related to *AI/ML* based on Durlik *et al.* [19.]: deep learning, artificial intelligence, reinforcement learning, Internet of Things, edge computing, predictive analytics, machine learning
- Terms related to *air emission inventories*: emission inventory
- Terms related to *seaports*: maritime, seaport, ship, vessel.

The search was conducted on September 15, 2024, and included only documents in English, with no restrictions on the time frame or location of the research. The initial search yielded 27 studies from Scopus and 9 from WoS. After removing duplicates and merging the results, 29 unique studies remained. Following the screening of titles and abstracts, 18 studies were selected. After full reading, the review resulted in a total of 13 included studies. Figure 3 illustrates the methodology, including the literature search process and the results.

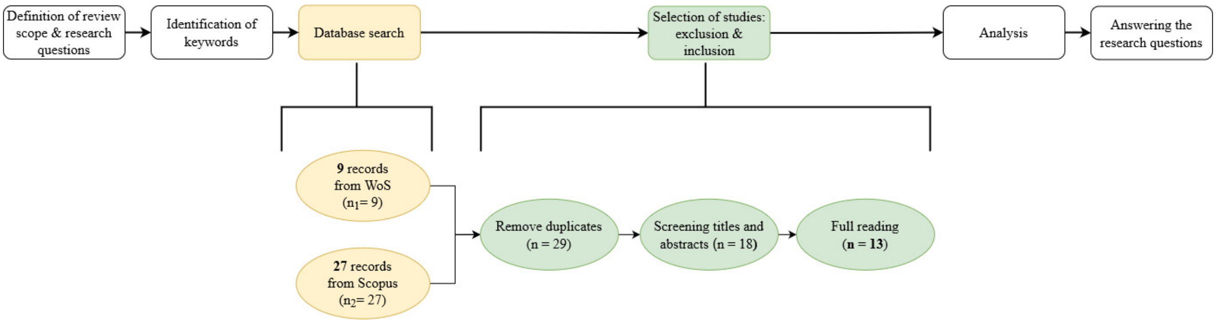

Figure 3. Methodological approach, literature search process and search results.

4. RESULTS AND DISCUSSION

Following the literature review, 13 scientific papers met the selection criteria. Figure 4 illustrates the annual number of scientific publications from 2017 to 2024. As anticipated, this topic is relatively new and not extensively explored, with the earliest paper dating back to 2017. Nevertheless, the trend indicates a growing interest in this area, demonstrating an expanding body of research. The papers meeting the selection criteria are detailed in Table 1:

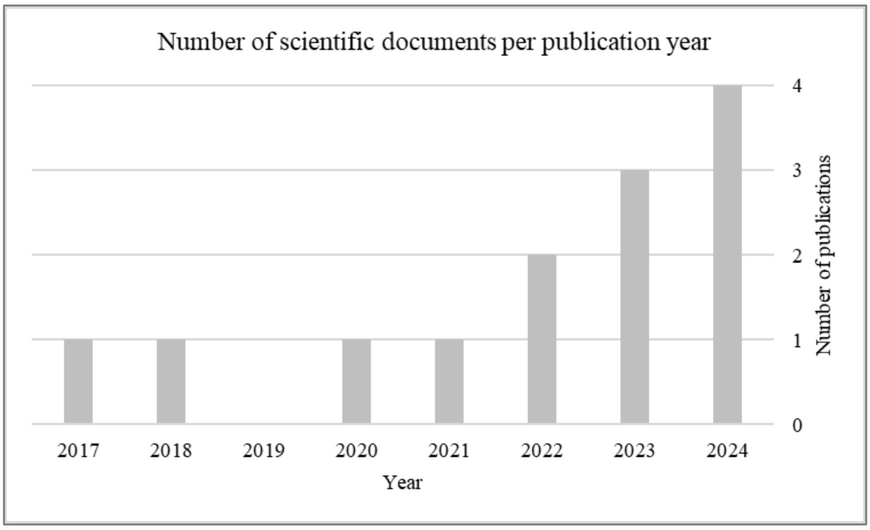

Figure 4. Yearly trends in the number of published scientific documents.

Table 1. Overview of seaport emission inventory literature: AI/ML techniques, objectives, and addressed challenges.

Reference	*AI/ML technique*		*Purpose to use AI/ML technique*	*Which barrier could be combat?*
	supervised	*unsupervised*		
[29.]	NN		To **estimate exhaust emissions** from ships under different navigational states	Achieve **accuracy** beyond existing EIs by pinpointing high-emission zones, peak emission periods, the most polluting ship types, and other valuable insights.
[30.]	GPR, LDS, SSPPLS, SMPPLS	PCA	To **improve the reliability of bottom-up approaches** by adapting to a wide range of dynamic input variables	**Quality of input data**: the emission factors are currently updated irregularly and are often sourced from vessel campaigns, which may not always reflect the technical details of applicable vessels. **Estimation ability**
[31.]	SVM, SVR		To **predict the delay** of vessels' arrival times	**Optimized landside and seaside operations** as well as their energy efficiency and emissions
[32.]	NN, DT		To **estimate the contribution** to worsened air quality of the overall port activity in the city of Barcelona by differentiating the isolated effect of each influencing factor on the concentration of pollutants	**Better accuracy**: by exploiting the vast amounts of data retrieved from citywide monitor networks **Saving computational resources:** only a typical personal workstation was needed
[33.]	NN		**To estimate the individual share of each pollutant source** as well as **the effectiveness of air pollution mitigation measures** at several locations across the metropolitan area of Barcelona	**Accurate prediction of local pollutant concentrations** by exploiting pollutant concentration and meteorology data sets without requiring detailed information on usually unavailable variables **Saving computational resources**
[34.]	SVR, LR, GPR		**To quantify emissions** from merchant ships and **to reveal the contribution** of maritime transport in the Istanbul Strait to the air pollution in this region	ML/AI methods offer considerable advantages, e.g., when processing large data sets, determining relationships between independent variables, and developing models.
[35.]	KNN, DT		To **predict carbon emissions** from ships	**Accurate CO2 emission forecasting** under different navigational conditions
[12.]	NN, LR, SVR		To **predict incomplete data** for port vessel EI	**Increase the precision of seaport EIs** by accurately predicting the missing data.
[36.]	NN		To **accurately forecast the critical emission parameters** of ships, including emission locations, time frames, and quantities	**Data-driven support** to formulate emission reduction strategies by forecasting CO_2, CH_4, and N_2O emissions. **Defining future emission scenarios** of ships within a reasonable margin of error
[37.]	Bi-objective optimization, VR		To **predict the optimal ship speed** by calculating the ideal fuel usage and shaft rotation	**Balancing out** economic and environmental benefits

				Balancing out the trade-off between ship operation costs and time
[38.]	Multi-objective optimization (IoT)		**To estimate the necessary variables** for accurately calculating emissions almost in real time, leveraging IoT-obtained databases in an automated manner	**Avoiding time lag** in building emission inventories by providing a methodology for building air emission inventories in real-time
[39.]	NN		**To predict NOx and CO emissions** of harbour vessels	**Significantly improved prediction accuracy** of NOx and CO emissions compared to the bottom-up method
[40.]	LR, DT, RF		**To predict HC emissions** from maritime ports as well as to identify the main contributors	**Unveiling the potential of data-driven methodologies** within seaports by elucidating emission trends and their determinants

Table 2. AI/ML techniques used in relation to EIs and their research paper applications by year.

AI/ML techniques	*2017*	*2018*	*2019*	*2020*	*2021*	*2022*	*2023*	*2024*
Neural networks (NN)	✓				✓	✓	✓	✓
Gaussian process regression (GPR)		✓				✓		
Linear dynamic system (LDS)		✓						
Supervised probabilistic latent variable regression (SSPPLS)		✓						
Supervised mixture probabilistic latent factor regression (SMPPLS)		✓						
Support vector regression (SVR)				✓		✓	✓	
Support vector machine (SVM)				✓				
Linear regression (LR)						✓	✓	✓
Decision tree (DT)					✓		✓	✓
K-nearest neighbour (KNN)							✓	
Voting Regressor (VR)								✓
Random forest (RF)								✓
Bi-/multi-objective optimization								✓

Despite the limited number of relevant scientific publications, the article analysis effectively addresses the research questions outlined in the introduction:

RQ1: What AI/ML techniques are considered by the selected literature? Table 2. highlights the evolution of AI/ML techniques used in emission inventories from 2017 to 2024. Several popular methods are commonly applied in EI, such as NN [12., 29., 30., 32., 33., 36., 39.], DT [32., 35., 40.], LR [12., 34., 40.], etc. Two articles examined more than one method in order to compare their efficiencies [30., 40.]. Techniques such as NN, GPR, and SVR gained increasing prominence over the years. While LR and DT started being used more in recent years, methods like KNN and VR appearlater. Additionally, techniques related to multi-objective optimization and RF were also applied in 2024, signaling diversification in the approaches for EI modeling.

Overall, there appears to be no clear consensus on which technique is most appropriate for specific issues, but certain trends can be observed. NN (specifically ANN–artificial neural network) is frequently used for emission forecasting and determining the individual share of emission sources from the total. MLR and SVM are often employed to make assumptions for incomplete data, such as fuel consumption. DT is applied to estimate the individual contribution to air quality and to predict carbon emissions from ships. Other models have been utilized for topics such as optimal ship speed and predicting ship arrival delays in addition to the aforementioned subjects.

A striking finding is the limited use of unsupervised ML techniques, with only one paper employing PCA. In this context, Fletcher *et al.* [30.] aim to simplify high-dimensional data by reducing its dimensionality and extracting key features, which are then used in (supervised) regression models to make predictions. Despite this example, the underrepresentation of unsupervised methods may have multiple explanations and warrants further investigation. Potential reasons for this underrepresentation include the complexity and interpretability of unsupervised methods [41.]. Additionally, supervised learning methods may be more suitable for the nature of the problems being addressed in EIs and thus more frequently employed. The availability of labeled data may also lead researchers to favor supervised methods.

Overall, the refined understanding shows a variety of applications and highlights the evolving preferences for specific methods in addressing diverse analytical challenges. Moreover, the increasing use of machine learning and artificial intelligence models underscores the demand for greater accuracy and reliability in emission inventories and predictions.

RQ2: Which barriers can be removed by using AI/ML techniques? The commonly used bottom-up approach to calculate emissions often suffers from insufficient data [34.] and irregular updates of the relevant emission factors [30.], which leads to an over- or underestimation of actual emissions [29.]. Thus, the integration of AI/ML techniques is primarily employed to supplement these calculations by forecasting emissions from ships and other seaport-related sources. That is a major advantage of AI/ML models in terms of their enhanced prediction accuracy compared to the bottom-up method [39.]. That has been demonstrated by Fabregat *et al.* [32.] by effectively predicting the individual impact of each source on pollutant concentration levels, even in the absence of detailed background flow states and pollutant inventories. By predicting emissions before they occur, decision-makers can proactively intervene, optimize processes, and implement strategic measures to mitigate or even prevent pollution [35.]. This underscores the importance of having reliable and accurate data to make such predictions [40.].

AI/ML techniques also enable the incorporation of a more extensive dataset and variables typically not available, e.g., local atmospheric hydrodynamics, surface heat flux, emission inventories of various types, including mobile sources, and urban layouts [33.].

In addition, despite the intense computational demands, using AI and ML techniques for predictions is considered to be more cost-effective [32., 33.], addressing one of the most significant barriers associated with implementing emission reduction measures in seaports [16.] and thus, with seaport-EIs.

RQ3: What improvements are required for the further use of ML/AI techniques? Methods such as deep neural networks and ridge regression should be tested further for their accuracy and appropriateness in EIs [40.]. Employing ML algorithms to test particulate matter emissions would significantly improve the precision and relevance of the estimated emission values.[30.].

To enhance performance and prediction accuracy, the models could be applied in one seaport but trained using data from another port. This approach would eliminate the need for an additional activity-based bottom-up calculation, thus saving time and resources. Beyond ships, the use of ML techniques could foster the integration of other modes of transport, such as rail [12.].

Although the techniques employed are well-developed, the frequently cited accuracy and reliability of emission inventories still rely heavily on the quality of the input data. The limited availability of data, due to the need for database subscriptions [38.], incomplete ship databases [29.], or due to the unwillingness to share sensitive data [40.], hampers the further advancement of AI/ML techniques in emission inventories. Addressing these issues requires not only technical solutions, e.g., integrating more effective digital devices with voyage data storage capabilities [35.], but also managerial measures, including data management practices and constructive cooperation with data providers and stakeholders [40.].

Some aspects not deeply discussed in the selected papers, but still relevant for further implementation of AI/ML techniques, are the technical and managerial challenges to contend with. With the growing datasets, cybersecurity is gaining increased attention and requires regulatory support [42.]. Additionally, existing infrastructure may not be compatible with new AI/ML techniques, necessitating flexibility and further investments. Key managerial challenges include employing skilled personnel, allocating resources for investment and maintenance, and managing both internal teams and external stakeholders for successful implementation.[43]

5. CONCLUSION AND OUTLOOK

As of today, artificial intelligence and machine learning are trending topics both in academia and in practice, driving the evolution and enhancement of both existing and future techniques. They are employed for various themes, also in the area of green ports and shipping. As demonstrated through the case studies of the Port of Rotterdam, Port of Los Angeles, Port of Singapore, and others, AI technologies have the potential to significantly improve emissions inventory practices, reduce environmental impacts, and enhance the operational sustainability of ports worldwide.

Based on a systematic literature review, this study explored the use of AI-driven technologies for air emission inventories in the context of seaports, a topic that has not been extensively researched until now. Drawing on the findings, the research questions were answered, helping to identify key trends, benefits, challenges, and future directions in the existing literature and providing insights into how AI can be leveraged to improve the accuracy and relevance of emission inventories.

By exploring the intersection of AI and emission inventories, this study contributes to the broader discourse on green port management and the role of innovative technologies in addressing environmental challenges. Despite the immense potential of AI techniques, e.g., improved prediction accuracy, numerous concerns have been raised. These include, e.g., lack of regulations necessary to achieve common European sovereignty [44.], insufficient education to prevent potential AI-related harms [45.], and issues of empowerment through automated decision-making [46.]. These and further concerns must be addressed with careful consideration.

While the research has some limitations, these may also help shape a future research agenda. Although the review highlights various AI-related challenges, it does not fully delve into a deeper analysis of these issues. Therefore, the proposed research agenda aims to explore specific managerial and technical concerns, examining practical case studies in detail. Additionally, surveys conducted with port authorities and sustainability representatives could provide a more comprehensive perspective on the practical difficulties of implementing AI/ML techniques in real-world scenarios and how to effectively utilize AI for implementing EIs. This approach will help to better understand and address the complexities associated with AI integration in this context.

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