Times of Ships in Container Ports: AIS Data for Maritime Transport and Ports Applications

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Abstract. In the context of a global trade, ports are critical nodes in the supply chain. For such reason, monitoring operations have a relevant role for both shipping companies and authorities. In particular, the time of ships in ports affects not only the performance of the ship but also the supply chain as a whole. So, it can be considered as an indicator of competition in the international trade challenge. Disaggregated and aggregated data related to different maritime activities can be used to evaluate this time. Thus, this study focuses on the innovation enabled by the introduction of automatic identification systems (AIS) and the use of data delivered by on board devices. AIS data provide information on the position of a ship allowing to analyze the activities of the ship within a port (e.g., the stop times). This paper aims to provide some general examples, taken from the literature, on the use of this type of data. From the analysis emerged that AIS data, since their introduction, have used for several scopes. Those can be broadly resumed into five different categories, referring to safety and security, environmental issues, route planning and shipping operations, data fusion and economical performances for both ports and vessels company strategies.

Keywords: automatic identification system · AIS · safety and security · route estimation · data fusion · port performance · literature review

1 Introduction

The volume of international seaborne trade reached 12,027 million tons in 2022, with a decrease of 0.4% compared to 2021 (UNCTAD, [1]). The rate of goods transported by sea is approximately 80% [2] of the total. In descending order, this volume is made up of dry bulk, oil shipments, and containerized trade. Therefore, the transport of goods is crucial in international trade [3], representing a pillar of the global economy. In fact, it has been seen (for example, the block of the Suez Canal, geopolitical tensions, wars) that obstacles to the maritime trade have repercussions throughout the world. Research on this topic covers different aspects: port management [4–6]; optimization of shipping operations [7–9], cost/time assessment [3, 10, 11]; the environmental impacts [12–14], the shipping services [15–17] and the use of new technologies [18–21]. In addition to this line of research, we can consider the cases of medium/short-range maritime transport (e.g., [22–27]), which in some cases support international seaborne trade (e.g., feeder

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O. Gervasi et al. (Eds.): ICCSA 2024 Workshops, LNCS 14823, pp. 253–268, 2024.
https://doi.org/10.1007/978-3-031-65329-2_17

services). Several research studies used data collected automatically from devices on board ships (e.g., [28–32]). In December 2000, the International Maritime Organization (IMO) updated the requirements imposed by the Safety of Life At Sea (SOLAS) international agreement [33] by introducing the use of an automatic identification system (AIS). This regulation (effective at 31 December 2004) is mandatory for all passenger and cargo ships in relation to the gross tonnage[1].

The AIS is a device capable of sending (receiving) information on the position of a ship, and the collected data can be used for different purposes (e.g., safety and security, emission estimation and other [35–41]). The rules established that AIS sends information (ship identity, type, position, speed, status, and safety-related information) to seaside stations, other ships, airplanes, satellites, and receives information from other ships. The mandatory use of such a device has made available data on naval activities that can be used in the field of research with multiple purposes [42–45]. The data provided by AIS (and the importance of international trade by sea) pushed the research on this topic; consequently, methods and models have been developed by using such data. Research ranges from safety and security and emission assessment to route evaluation and design. Figure 1 shows a possible classification of the AIS data to be used in the research. It differentiates between historical and real time and also considering the possibility to gather data from multiple sources. Thus, it is possible to identify some topics frequently treated in the literature.

1. Risk assessment;
2. Emissions assessment;
3. Route estimation and planning;
4. Data fusion;
5. Ports and ships performances.

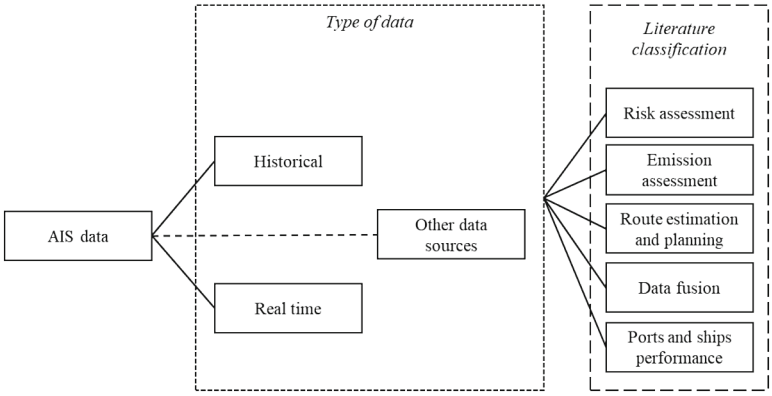

Fig. 1. AIS data and applications.

[1] *Ships fitted with AIS shall maintain AIS in operation at all times except where international agreements, rules or standards provide for the protection of navigational information* [34].

The rest of the paper follows the previous classification, dedicating a paragraph to each of the previous points. Section 2 contains papers on the topic of risk assessment, Sect. 3 summarizes papers on environmental emission assessment, Sect. 4 is on ship route estimation and planning, Sect. 5 contains some studies on the use of AIS integrated with other databases, while Sect. 6 contains some studies on ports and ship performance. Finally, the conclusions.

2 Risk Assessment

An element in defining the risk of collision between ships is the domain of the ship, intended to be the domain around a ship where other ships avoid entering. Therefore, the definition of the domain may be useful in risk assessment. As an example, Kundakçı et al. [46] proposed a domain model based on the type of ship and on different safety criteria. The relative positions between the ships were analyzed, and changes in the domain size of the ship based on ship type and size were highlighted. Bye and Almklov [47] used historical AIS data to provide some normalized statistics on maritime accidents, focusing the study on two events (groundings and allisions) and for two categories of ships (cargo and passengers). The paper focuses on strategies to monitor the level of risk and develops some strategies to mitigate it. Altan and Otay [48] focused their study on collisions between ships on congested waterways by using a collision model (from molecular theory) that takes historical AIS data and gives as output a probability of encounter. The results of the model are compared with the observed data. Oruc and Altan [49] analyzed risk patterns due to the encounter of ships on narrow waterways. The interactions between ships are explored starting from AIS data and using an unsupervised learning algorithm to determine the risk value. Similarly, Zhang et al. [50] proposed a convolutional neural network to classify the risk of collisions. The proposed framework consists of two levels: at the first level the potential collision events are extracted from the AIS data, this information represents the input for the second level that provides a risk rating for collisions. Liu et al. [51] proposed a multi-step analysis for assessing collision risk based on game theory. The first step consists of identifying the collision risk of each ship in a cluster by pairwise analysis. Then, the analysis is extended considering the contribution of each group to the risk value.

Zaman et al. [52] analyzed traffic conditions in the Singapore strait over the time classified by ship type. The aim consisted in monitoring the flow along the waterway and provide support in improving ship risk in the strait. Similarly, Wu et al. [53] studied the behavior of ships approaching a hotspot in narrow and busy waterways considering different types of trips and linking speed with density. The goal is to estimate the risk of ship collisions at hotspots. Mou et al. [54] proposed a statistical model based on historical AIS data to simulate collision among ships in a port. The predictors used in the regression model include ship characteristics, course characteristics and speed. Liu et al. [55] introduced an analysis method to assess the risk of ship collisions based on static and dynamic AIS data. The approach is non-linear and the collision risk is obtained by integrating the position vector and the speed of the ships.

Considering the case of ships sailing in open water, Zhang et al. [56] proposed a method to evaluate in real time the probability of a ship collision using AIS data. The

approach focuses on autonomous maritime surface ships and uses a distance indicator to classify risk in different situations. Similarly, van Iperen [57] developed methods based on distance and time to classify ship encounters (distinguished into head-on, crossing, and overtaking encounters, also considering the routes structure) and monitor ship safety. Feng et al. [58] proposed a method for assessing collision risk based on AIS data within a port. The approach is based on the calculation of the entropy and clustering. The conclusion is that the method could be used to improve the safety level. Rong et al. [59] studied the behavior of ships in avoiding an accident, the procedure is based on AIS data used to recognize those cases where the accident was avoided. A sliding window algorithm is applied to identify the moment in which the ship performed an evasive maneuver to avoid colliding with another ship. Zhu et al. [31] have proposed a framework to classify ship encounters and some predictors are selected in order to estimate a model. A sensitivity analysis approach is applied in the phase of predictors selection. Zhao and Fu [60] proposed an index for the assessment of real-time collision risk based on AIS data. Such an index aims to establish if two ships can collide while maintaining the current state of motion, so the obstacle's speed is considered a fundamental element in the index definition. An improvement of the previous approach has been proposed by Chen et al. [61]: the proposed method considers that the obstacle travels with non-linear variable speed. Note that, in this method, the encounter between two ships is considered as a process that takes into account the spatio-temporal relationship between them. Chen et al. [62] propose an extension of this work, taking into account the encounter of multiple ships, is proposed by Chen et al. [62].

AIS data are also useful for analyzing the risk faced in collisions between ships and fixed structures (e.g., bridges). As an example, Zhao et al. [63] consider the risk connected to the collision between a ship and a bridge, and the AIS data are used to obtain the attributes (such as speed, position, etc.) to be putted in the model. The model is based on the finite element approach. Xiao et al. [36] investigated the risk of collision between ships and bridges on some waterways in China. AIS data are used to individuate traffic conditions, and the interaction among different ships is simulated through a multi-agent model. To understand ship behavior, two different cases studies are simulated and compared. Cai et al. [64] proposed a model to assess the risk when a ship crosses a river considering different elements, such as the distance to the closest point of approach and the time to the closest point of approach. In a similar study, Wang et al. [65] proposed a method (based on real-time AIS data) to model ship flow characteristics and estimate the correlation between speed and flow. The aim is to obtain an estimated value of the speed to compare it with the limitation imposed by the traffic regulation. Horteborn and Ringsberg [66] studied possible ship allision against a bridge, considering three possible scenarios: drifting ship, sharp turning ship and miss of turning point. The scenarios are simulated using the Monte Carlo approach.

3 Emissions Assessment

Ship emissions attract attention worldwide, and several methods (e.g., [67]) are used to quantify them. AIS data can support this task by providing ship and route data (e.g., engine load factors). Indeed, AIS data allow for separating the ship's activities (ship

at anchor, ship docked for load/unload operations, port arrival/departure) and linking them with the estimation of ship emissions [68]. Procedures based on such data are often indicated as bottom-up approaches. Tian et al. [69] demonstrated the impact of AIS data thinning in the emissions, namely, how the amount of data used in emission estimation of emissions affects the quality of the results. The conclusion is that the data must be thinned differently depending on the position of the ship (e.g., in port, coastal navigation, etc.). Ng et al. [37] exploited data from AIS (and, in particular, ship movement and speed information) to estimate the engine load factor used, together with data from other sources, to assess ship emissions. The procedure is also aimed at supporting decision makers in policy planning. In Tichavska and Tovar [70] the AIS data are used to geographically locate the emissions in a port. The procedure identifies the activities of a ship (in berth, in maneuver) and puts them in the procedure for emissions inventory. The aim is to classify the emissions in a port according to their location to assess the policies (environmental, operational, or political) aimed at minimizing the environmental impacts. Furthermore, the procedure supports monitoring of the effects of such policies. In Bojic et al. [71] a model to estimate ship emissions in a port has been proposed; the AIS data are crossed with ship technical details. Huang et al. [72] extended the previous approach by proposing a spatio-temporal approach to estimate emissions. The proposed model differentiates among ship classes and navigation states. The model has been tested using a port as a case study. Chen et al. [73] focused their study on the contribution of ships on the particulate matter concentration in the city near the analyzed port (about the 13% in summer). A classification of emissions based on the type of ship is also provided, highlighting that container ships are the main contributor to emissions in the study area. Peng et al. [74] applied the power-based emission inventory calculation using AIS data to obtain the emissions in the urban area near the port. The model is updated by introducing a correction coefficient for the engine propeller to optimize the results. Toscano et al. [75] investigated the activities and emissions in the Naples port through AIS data, obtaining a temporal trend of the emissions. In addition, they used a dispersion model to assess the impact on the nearby urban area. Li et al. [76] estimated the emissions considering different types of ships, taking also into account the influence of speed on emissions (and, consequently, the influence of the different ship operational activities). A spatio-temporal analysis of emissions is provided. Similarly, Chen et al. [77] developed a spatio-temporal emission inventory and analyzed the emission variation within a month using the uncertainty estimation procedure. Variation in emissions over time is attributed to variation in the quantity of freight transported. Huang et al. [78] introduced a method to develop AIS data in real time to obtain the ship emissions from the ship route. The approach provides results in the spatio-temporal domain. Goldsworthy and Goldsworthy [79] used terrestrial AIS data to develop a model to estimate emissions and to allocate them spatially (in port and in coastal waters). Emissions are calculated by ship characteristics (type and size), operating mode, and engine type. This analysis has been extended in [80], where a method based on the search for the shortest path has been used to improve the estimation of the spatial distribution of pollutant elements. Woo and Im [81] proposed a bottom-up approach based on AIS data to assess emissions in a port over time. The authors correlated the emissions with the speed of the ships in the port, demonstrating that a speed regulation would reduce emissions. In a similar work,

Woo and Im [82] used AIS data to estimate the spatial distribution of emissions in real time. The goal is to verify the efficiency of the ship speed reduction policy in reducing emissions (in the real-world application, the spatial analysis showed the reduction of emissions with the reduction of the speed). Kim et al. [83] calculated the volume of emissions from ships in a port considering separately activities (cruising, maneuvering, hoteling) in order to estimate the engine load factor of the engines. The activities of the ship in the port are determined by analyzing the AIS data. Jiang et al. [84] proposed a model to calculate the emission from ships in the inland areas. As in other similar models, the emissions are calculated for the different activities of the ship in port. Cheng et al. [85] used AIS data to assess the emissions in a port and verify the results of a policy aimed at reducing the emissions of ships in the port. The conclusion is that the contribution of the ship in emissions was reduced (mainly in terms of SO_2 and PM) by applying this policy. Kao et al. [86] estimated the emission over time considering different scenarios (e.g., speed reduction). The aim is to improve environmental conditions, at the port, allowing us to identify the elements on which to intervene to reduce emissions. To estimate ship emissions in port, Chen et al. [87] proposed a model based on ship activities. In particular, AIS data are used to identify the operation in port (dock, undock, maneuver), and the emissions are estimated separately for each activity.

4 Route Estimation and Planning

Today, maritime transport is becoming an essential stream in global trade. Several scholars focused their work on AIS to exploit the information contained therein and propose data-driven predictions on arrival and operating times.

Yin et al. [38] developed a model to forecast the destination of the ship by combining historical and real-time AIS data. Ma et al. [88], proposed a neural network approach in which the trajectories were first extracted with a clustering method and then developed a forecast procedure based on neural networks. Similarly, Wen et al. [89] used AIS data for the design of ship routes, applying cluster analysis to individualize waypoints and the neural network to generate routes (also considering different dimensions of the ship). Chen et al. [90] proposed a deep learning approach by crossing speed and position information as a training input for the neural network. The aim consisted in improving fitting accuracy of the observed routes. In addition, the missing points of a route are correlated with the known points near routes, if available. Mehri et al. [91] proposed a model based on deep neural networks to individuate the trajectory of the ship and to foresee ship position (using as input the type of ship and geographic information). Wang et al. [92] developed a cluster analysis to extract routes from AIS data taking into account the density of ships. In addition, an approach to determinate the optimal number of clusters is provided. To consider the ship behavior in trajectory estimation, Wei et al. [93] proposed a procedure based on an algorithm to simplify the trajectory of the ship (related to the data on the position of the ship) and on a sliding windows algorithm (related to the variation of the course and the ship characteristics). Yan et al. [94] proposed a method (based on a semantic model) to individuate ship routes based on historical AIS data and used graph theory to provide a simplified representation of such routes. The aim is to forecast the traffic of the ship and analyze the activities of the ship.

Guo et al. [95] proposed a kinematic interpolation method (KI, [96]) to reconstruct the trajectory of the ship using AIS data. The approach starts from the search and elimination of incorrect data, and it individuates the trajectory by using an improved version of KI. Such a version of the interpolation procedure also provides for the reconstruction of missing parts of the trajectory. A multistep prediction model has been proposed by Gao et al. [97] to estimate the trajectory of a ship. The historical data are used to identify a support trajectory, starting from a point of them the next point is calculated by cubic spline interpolation. Another aspect that can be considered is the distance between similar routes collected with AIS, with this in mind, Luo and Zeng [98] proposed a framework to measure the distance of the ship trajectory based on a neural network. The procedure has been tested on a real trajectory dataset. Filipiak et al. [99] presented a method to obtain a maritime graph (consisting of nodes and links) based on historical AIS data. The approach starts from the detection of maneuvering points and waypoints (intersection between different routes) and builds the links. The maneuvering points are individuated by using a cumulative sum approach, while the waypoints are the output obtained by applying a genetic algorithm to the set of maneuvering points. Lee et al. [100] proposed a method to obtain routes and waypoints based on cluster analysis and kernel density estimation. In their work, the authors individuated, for each route, the vertices among which the waypoints will be identified.

5 Data Fusion

Sometimes, AIS data are integrated with other data sources to obtain more accurate results. As an example, Liu et al. [101] combined AIS with data from SAR (Synthetic Aperture Radar) to identify oil spill pollution. For tracing oil discharge from ships, a framework is proposed in which the SAR is used to identify suspected oil slicks (time, location, range). Then, the suspect ships are individuated by combining oil-sick trajectory simulation and data from AIS (in a time slice after the identification of the oil). Similarly, Pelich et al. [102] proposed a procedure for ship monitoring based on SAR data and used AIS data to validate the results (in fact, the objective is to evaluate the accuracy of satellite observation in relation to the dimension of the ship). Asborno and Hernandez [103] used historical AIS data and aggregated port throughput data to estimate the quantity of freight transported by ships for each travel. The study focuses on inland waterways with the aim of reducing freight flows and (eventually) supporting decisions about investments in transportation infrastructures. Huang et al. [104] integrated AIS data with ocean environment information (such as winds, waves, and currents) to estimate ship emissions. This approach allows to consider how the environment affects the activities of the ship, increasing the performance of ship activity-based method used to estimate the emissions. Abebe et al. [105] integrated AIS and marine weather data with the aim of forecasting ship speed, the approach used is based on machine learning. Different techniques of machine learning are used, in order to compare the accuracy of each of them. Wang et al. [65] combined AIS data with waterway data to simulate the flow of the ship and correlate them with speed. The main goal is to compare the forecasted speed with that required by maritime regulation. To predict the ship trajectory, Borkowski [106] proposed an algorithm that takes advantage of current ship position collected by

several devices, and AIS is among them. The data fusion is based on Kalman filter, and the procedure works using a generalized regression neural network. Kaklis et al. [107] presented a method for the design of the route of ships using historical AIS data. An algorithm for the route search is implemented to find the optimal one to compare with the observed one. AIS data are integrated with real-time weather condition data; the goal is to optimize the route and also considering environmental conditions. Li et al. [108] crossed AIS data with VIIRS boat detection (VBD) to monitor the activities of fishing boats; the aim is to identify the fishing by zone over time. Thoya et al. [109] proposed a method to estimate fishing activities by combining AIS data and the vessel monitoring system (VMS). The aim is to identify discrepancies between the two databases and integrate them to have a more accurate analysis of the studied area. The correlation between fishing activities and oceanographic elements is investigated by Li et al. [110]. The AIS data are integrated with satellite-derived sea surface temperature (SST) and chlorophyll a concentration.

6 Ports and Ships Performance

AbuAlhaol [111] proposed a data mining framework to obtain three indicators (spatial complexity, spatial density, and time of service) to quantify port congestion. Historical and real-time AIS data are as an input; the approach combines these two data sets and gives the indicators as output. Chen et al. [112] defined some port performance indicators (port productivity, ship traffic, berth utilization) and proposed an approach (based on AIS data) to evaluate them. The study focuses on container ports to identify infrastructure weaknesses and intervene with appropriate policies and procedures to improve productivity and optimize liner scheduling. Chen et al. [113] have proposed an approach based on the sliding window algorithm to evaluate the congestion index of a port. In it, the AIS data are used to explore the ship's trajectory in the port: from this, the time in port and the related monetary costs are evaluated. De Langen et al. [114] proposed an index to measure the connectivity of roll-on roll-off ports by using, among others, AIS data to individuate the ship route and the related travel time. Similarly, Jia et al. [115] proposed a connectivity index considering different ship types; such an index depends on the number of port calls, the rate of international traffic, and the characteristics An approach able to estimate the port locations and related operational zones has been proposed by Millefiori et al. [116] by using historical AIS data and a distributed machine learning method. The approach is tested in an existing port. Peng et al. [117] proposed an evaluation model to assess the competitiveness of a port, using geographic data and AIS data. The method is based on the concept of entropy and considers ship trajectories, infrastructural facilities of the port, and socio-economic data. Feng et al. [118] proposed a framework for estimating the time a ship spends in a port that exploited the ship trajectories provided by AIS data. The time estimation is provided for different port zones and vessel categories, and performance indicators are defined to assess the payload productivity. Jia et al. [119] proposed a methodology based on the ship draught information (collected from AIS) and ship and travel-specific information to estimate the ship's payload. Lee et al. [120] studied the ship trajectories in a port exploiting AIS data, distinguishing ship arrival and departure. A clustering method is

applied to search for possible patterns in the analyzed trajectories. Liu et al. [121] combined principal components analysis, a clustering approach, and a soft dynamic time wrapping method to identify ship trajectories, separating in-port and out-port ship routes. The input data comes from historical AIS data.

7 Conclusions

This paper reviews the current use of the AIS data in maritime analyses. From this literature emerged how versatile result AIS data are. It emerged that one of the primary uses consisted of collision risk assessment analyses whose approaches range from statistical analysis to neural networks to microsimulation. Another highly-covered topic concerns environmental analyses and carbon emissions. Some approaches were thought to find the emission inventory for vessels in navigation and others for vessels in port (in this case, the emissions are estimated for each type of activity of the ship into the port). Data collected from AISs are often used in planning operations to evaluate effective policies to reduce air and noise pollution. Therefore, the data from AIS are used to estimate/optimize the route, for example, to reduce the ship's travel (and related impacts). The approaches used contain neural networks, cluster analysis, and heuristic approaches. Often, AIS data are integrated with other data to increase the database and improve the quality of the results obtained.

The emerging availability of real-time data offered by AIS devices enabled the possibility of enriching analyzes to estimate the time of ships in port. For example, the AIS data allow the analysts to infer the various activities carried out by the ship and the identification of possible predictors to use in the models (for example, type of ship, size of the ship, period of the year). Even if AIS data till today are not fully explanatory to assist the analyst in such a compelling domain, and other data, as well as information on terminal equipment and facilities, are necessary to unveil different segments of activities that took place in container ports; the introduction for AIS data offered the opportunity to deliver a valuable tool to overcome the limitations imposed by direct surveys and the restrictions related to the use of data provided through VTS systems whose nature is confidential and for exclusive use by the authorities.

Acknowledgments. This study is carried out within the research project "National and local factors affecting times of ships in container ports", Piano Nazionale di Ripresa e Resilienza (PNRR), Next Generation EU. Progetti di Rilevante Interesse Nazionale PRIN_2022_PNRR_P202292YFW. CUP: C53D2300878001. This presentation reflects only the authors' views and opinions, "neither the European Union nor the European Commission can be considered responsible for them".

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.

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