AIS Data Analytics for Shipping Business Decision-Making: A Short Survey

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Abstract
We present a survey of AIS data analytics techniques for shipping business decision-making. Our survey provides an indicative categorization of the areas where AIS data analytics may assist in strategic decision-making, based on the costs that a shipping business needs to cover. These areas include chartering and freight markets, vessel operation and environmental footprint. Our survey is useful both as a catalogue of existing research, as well as a critical evaluation of the field. The use of AIS data has facilitated the state-of-practice in shipping business decision-making. Furthermore, enriching AIS data with other data sources is necessary more often than not.

Keywords
Chartering Decisions, Vessel performance, Maritime Information Systems

1. Introduction

More than 80% of global trade by volume and over 70% by value is carried by sea [1]. The shipping business is a global, highly-competitive and cyclical industry that involves heavily leveraged assets, exposing shipowners to various business risks that require timely decision-making [2]. For these reasons, exploiting the benefits of maritime informatics [3], primarily through the analysis of Automatic Identification System (AIS) data, forms an important tool for shipping companies striving to place themselves in front of the competition and survive the shipping business cycle [4]. For instance, maritime data analytics can support: a) optimal steaming for just-in-time arrivals, b) reduction of unnecessary waiting times by enhancing coordination, c) efficient utilization of human resources, d) service providers and service consumers while establishing market-based business deals, e) predictive maintenance based on digital twins of critical assets and their components, and f) optimized cargo planning [5].

The International Maritime Organization (IMO), under the Safety of Life at Sea (SOLAS), has adopted AIS across several other reporting systems associated with tracking vessels. There are 64 different types of AIS messages divided into two main categories: static messages, including e.g. the IMO number, name of the vessel, type of the vessel, dimensions, estimated time of arrival, draught and destination, and dynamic messages, including the Maritime Mobile Service Identity Number (MMSI), rate of turn, speed over ground, position coordinates, course over ground, heading and navigational status. The use of AIS data supports a wide range of applications in the shipping industry. These include, among others, collision avoidance, fishing fleet monitoring, maritime security, infrastructure protection, trade analysis, as well as ship and port performance. Lee et al [6] reviewed the historical developments of AIS applications in the management of waterways, natural resources, freight and ports. In a similar spirit, Svanberg et al [7] provided a structured overview of various AIS applications, including interactions with natural resources (e.g., species, fishing and ice), collision avoidance, oil spills' investigation, as well as traffic and logistics analysis. Yang et al [8] reviewed some applications of AIS data analytics, including navigation safety, trade analysis, fishing activities, environmental evaluation, oil spill risk analysis, and ship and port performance. Emmens et al [9] and Bereta et al [10] examined the promises and perils of AIS data, including unrealistic tracks, vulnerability to external conditions, inaccuracies by human input, attacks, as well as intentional communication gaps .

We present survey of AIS data analytics for decision-making in the shipping business. Due to space limitations, we chose to focus mostly on the literature of the maritime domain for the benefit of the Data Scientist. Our survey provides an indicative categorization of the areas where AIS data analytics may assist in strategic decision-making, based on the costs that a shipping business needs to cover. We discuss how AIS data may be used for vessel chartering decisions, the assessment of vessel operation, maritime trade, and environmental im-

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pact calculation. For each area, we provide an overview, and a synthesis of the main contributions and limitations. In other words, our survey is useful both as a catalogue of existing research, as well as a critical evaluation of the field.

2. Survey Structure

We classify the AIS data analytics approaches into five areas. Table 1 summarizes, for each approach, the employed data types, the geographical and temporal coverage of the empirical analysis, as well as the vessel types for which the analysis was performed. (All aproaches have employed AIS data, and thus this is omitted from the table to save space.) We start the survey by discussing the area of chartering and freight markets (see Section 3). Freight rate revenue is the principal source of repayment in connection with ship financing, impacting liquidity and profitability ratios that financiers use to monitor the performance of a shipping loan. In this context, shipping business decisions are influenced by the economic cycles and the volatility in demand, impacting freight rates and ship values for different segments of maritime transport, law regulations, risk profiles and ownership requirements.

In Section 4, we discuss the vessels' operation. Shipping companies use key performance indicators (KPIs) to monitor and analyze the performance of each vessel, such as the number of overdue planned maintenance tasks. Due to the high market competition, this process should be completed quickly. For this reason, the traditional daily noon reports are insufficient. Instead, AIS data can contribute to minimizing the time required for assessing vessel operation.

Maritime trade analysis, discussed in Section 5, can identify commodity flows and ship trading patterns representing the different shipowners' and charterers' behaviors. Events like the COVID-19 pandemic, Oil Glut (2014-2016), and the financial crisis of 2008-2009, can be used to study freight flows as examples to avoid future crisis situations.

Finally, shipping environmental impact analysis, as presented in Section 6, demonstrates the increasing interest in sustainability. Shipping companies evaluate ESG (Environmental, Social, Corporate Governance)-related KPIs, mainly concerning the investment required to decarbonize and operate in terms of reduction of CO_2. Sustainability can potentially impact cash flows, the collateral value of a ship, and, therefore, the value-to-loan ratio. ESG initiatives and investments are opportunity costs impacting the predictability of capital, operational and voyage costs. Failure to comply with targets and thresholds may result in fines, higher interest rates, additional capital injections, higher fees to port agents, delays and rectification of incidents.

3. Chartering and freight markets

3.1. State-of-the-art

In this section, we discuss the use of AIS data for supporting the chartering decisions of shipowners and charterers. Adland et al [25] provided a theoretical exposition and empirical analysis of the micro- and macro-economic determinants of vessel capacity utilization in bulk shipping markets. One step further, Sugrue et al [20] suggested a linear model to predict vessel capacity based on water surface elevation. In an effort to gain further understanding of the freight market, it is important to derive the actual demand and supply balance. Towards this, Prochazka et al [18] provided a prediction of the demand and supply balance in the freight market, based on historical and online AIS data. In the same vein, Regli et al [16] proposed a method for calculating the short-term capacity in the voyage charter market based on the ratio of available to active vessels. They investigated the percentage of vessels available for orders by using AIS draught measurements.

Bai et al [56] explored the effectiveness of risk management strategies for mitigating risk exposure to freight rate and bunker fuel prices, using vessel and voyage-related data. In this context, Prochazka et al [15] investigated the factors affecting the preferable fixture location, such as market conditions, vessel characteristics, and charterer's preferences. Bai and Lam [12] explored the impacts of selected attributes (i.e., freight rate, commodity price arbitrage, bunker price and the number of ships in a specific area) on the charterer's destination choice. Jia et al [13] used machine learning techniques to predict the destination for crude oil exports. They investigated the micro- and macro-level determinants of the preferable destination. In a similar study, Zhang et al [19] suggested a data-driven model for vessel destination prediction based on the similarity between the current trajectory and historical trajectories. Regli et al [17] identified the vessel specifications that affect the charterer's decision to exploit storage arbitrage opportunities using historical AIS data.

3.2. Contributions

In most cases, the AIS draught measurement has been used for estimating the cargo payload of a commercial vessel — this is a key variable calculating revenue for a particular voyage and estimating global trade flows for commodities. AIS draught measurement was also used to distinguish between laden and ballast voyages. More accurate calculations for cargo payload estimation may be achieved by combining AIS draught measurements

Table 1
Data types, geographical and temporal coverage

Theme	Subtheme	Literature	Data types	Region	Vessel types	Period
Chartering and freight markets		[11]	Port	Brazil	Commercial	2008-2014
		[12]	Freight,cargo	Global	Commercial	2013-2017
		[13]	Cargo, vessel	Latin America	Commercial	2013-2016
		[14]	Port	Australia, Brazil, China, India, and South Africa	Commercial	2012
		[15]	Fixtures	Persian Gulf area, West Africa, Venezuela	Commercial	2019
		[16]	Port	-	Commercial	2014-2016
		[17]	Vessel, fixtures, freight, derivatives	Ras Tanura in the Arabian Gulf to Chiba in Japan	Commercial	2014-2016
		[18]	Fixtures	North-East Asia to Australia	Commercial	2016-2019
		[19]	Port	Global	Commercial	2011-2017
		[20]	Vessel load	Great Lakes	Commercial	2015-2017
		[21]	Vessel, port	Global	Commercial	2012-2020
Vessel operation		[22]	Freight, fuel	Global	Commercial	2013-2015
		[23]	Fuel	North Sea Emission Control Area	Commercial	2013-2015
		[24]	Weather	Port of Rotterdam	Commercial	2009-2011
		[25]	Port, fuel, freight	Global	Commercial	2011-2012
		[26]	Weather	Nieuwe Waterwag	-	2014
		[27]	Weather, insurance	East Asia and North America	Commercial	2013-2019
		[28]	Fixtures	Brazil to China route	Commercial	2015-2019
		[29]	SAR	English Channel, UK	-	2017
		[30]	-	Denmark	Commercial	2022
		[31]	-	Zhoushan Port	Commercial	2016
Maritime trade		[32]	Cargo	Global	Commercial	2013-2016
		[33]	-	Netherlands	-	-
		[34]	-	Qiongzhou Strait	-	-
		[35]	-	Suez Canal	Commercial	2013-2019
		[36]	-	Global	Commercial, Passenger	2016-2019
		[37]	Vessel, weather	Global	Commercial	2017
		[38]	Port	Global	Commercial	2016
		[39]	Vessel, freight, fixtures	Global	Commercial	2017-2020
Environmental Impact	Emissions Calculation	[40]	Vessel	Madura Strait	Commercial, passenger	2008
		[41]	Vessel, technical, fuel	Hong Kong, Pearl River Delta	Commercial	2007
		[42]	Fuel, weather	Arctic Seas	-	2012
		[43]	Vessel	Global	-	2015
		[44]	Vessel	Pearl River Delta	-	2015
		[45]	Technical	Yangtze River	-	2018
		[46]	Fuel	North and Baltic Sea	Commercial, passenger	-
		[47]	Vessel, technical	Trieste	Commercial	2018-2019
		[48]	Vessel, technical	China	Commercial	2019
		[49]	Vessel, technical	Singapore	Commercial	2016
	Fuel consumption measurement and savings	[50]	Port	Port of Gothenburg	Commercial	2014
		[51]	Noon reports	Global	Commercial	-
		[52]	Weather	Global	-	2014
		[53]	Fuel, technical	Global	Commercial	2018-2019
		[54]	Vessel, port	Ports in European Economic Area and United Kingdom	Commercial, passenger	2018
		[55]	Port	Norway	Passenger	2018

“-" indicates that there are no available details about the field.

with additional indicators, such as the number of ships waiting for a contract, the number of days the ships are waiting, the vessels that are on dedicated routes and do not contribute to the spot market voyages [18, 12, 17]. The ratio of available vessels to active vessels is a potentially helpful indicator of shipping economic activity and, as such, may be used more widely as a freight rate forecast indicator and a proxy for trading and physical market activity [17].

The analysis of historical AIS data related to operational risk management strategies (e.g., fleet diversity, fleet age, relative trip distance, fleet repositioning flexibility and trading diversity), allows shipping companies to draw valuable conclusions [56]. The models proposed for AIS data-driven destination prediction may be classified into two categories: a) the turning point-based destination prediction methods, and b) the trajectory-based destination prediction methods [19]. For instance, predicting oil export destinations allows for better forecasting of regional and local market balance, improved knowledge of inventory levels, and monitoring of the supply chain. The model proposed by [14] has an accuracy ranging between 70-90%.

3.3. Limitations

The use of AIS data seems to lead to much better accuracy than the use of traditional noon reports, as a) errors due to human input are reduced, and b) information can be obtained in an online fashion. On the other hand, an important limitation of several studies examining chartering decisions concerns the fact that there is no commercial information available through AIS, such as information about about the cargo and charter-parties. Publicly available fixtures and freight derivatives information covers only a tiny fraction of the voyages observed in AIS data [21, 18, 15, 17]. Moreover, in many studies the matching process of AIS data and fixtures data is based on the vessel name because the IMO number is not part of the fixture reports. This can be problematic since the ship's name may change, while many ships may bear the same name [18]. One way to address this issue is to consider other static vessel attributes, such as the vessel's type and dimensions.

In any case, the methods that estimate the cargo payload by using AIS measurements have additional limitations — consider, e.g., the difficulty of measuring ballast water and fuel during draught measurement [14].

4. Vessel operation

4.1. State-of-the-art

Vessel monitoring is essential for performance estimation as well as for controlling her activities. In this section, we discuss the research focusing on the evaluating vessel behavior. An important feature when operating a vessel is speed selection, due to the costs involved as well as its relevance to commercial and charter-parties' terms. Early research by [22, 25] investigated technical, operational, and macro-economic variables concerning the vessel's speed using a regression model. Adland et al [23] attempted to prove, with the use of dynamic AIS data, that the introduction of stricter regulations of an Emission Control Area has no effects on vessel speed. Prochazka et al [28] investigated how contractual obligations affect the speed of vessels. Shu et al [24] quantified the influence of weather conditions and vessel encounters on vessel speed, course and path within ports and inland waterways.

In addition to the study of the normal behavior of ships, the maritime community is also interested in the study of anomalies [57]. In this context, in a recent study, Zhang et al [31] proposed a dynamic maritime traffic pattern recognition model that adapts to the changes in the traffic environment. Finally, despite the usefulness of AIS data for monitoring ship behavior, data is often missing due to human negligence or intention. In this context, Zhou et al [26] investigated the impact of wind and sea currents on ship behavior within ports, where vessel trajectories can be observed, using ship maneuvering information provided by dynamic AIS data. Rodger et al [29] suggested a methodology to map ships which do not report their AIS information using SAR ship detection.

4.2. Contributions

In addition to the aforementioned contributions, there were efforts towards data pre-processing in order to increase data reliability [26, 25, 22]. Furthermore, to distinguish between the different vessel's operational modes, an effort was made to distinguish stops at anchor and stops at berth [54]. The efforts to model the behaviour of dark vessels is also noteworthy, since communication gaps are increasing over time and often associated with illicit behaviour.

4.3. Limitations

The use of AIS data alone is rarely sufficient for the assessment of vessel operation. AIS data must be enriched with information from additional sources, such as meteorological [27, 25, 22], commercial [25], maintenance [22], technical [24], management, flag and port data [27]. Consequently, the studies based solely on AIS data often have limited significance. Furthermore, it has been difficult to determine the point at which a ship passes from laden to ballast state, thus the semi-laden voyages are ignored [54, 25]. While the approaches discussed in this section offer valuable insights on the benefits of AIS data analytics for vessel operation assessment, their conclusions are mostly drawn from studying specific geographical regions (see Table 1). Thus, it is not clear whether they can be generalised to other or larger areas.

5. Maritime trade

5.1. State-of-the-art

We outline some key empirical studies of the analysis of commodity flows based on AIS data. Adland et al [23] compared the accuracy of AIS-derived trade statistics against official customs data in the crude oil market. Kanamoto et al [38] analysed the global trade flow pattern of dry bulk cargo by commodity. They suggested a model to forecast the future shipping demand by vessel type and commodity. Yan et al [37] calculated the oil trade volume by establishing a model for cargo payload calculation based on draught and vessel's technical information. Fuentes et al [35] proposed a recognition model of anchored vessels waiting for transit from Suez Canal. They identified the access routes from anchorages based on AIS draught measurements. Li et al [39] proposed a machine learning technique to predict the cargo type transported by coated product tankers.

Existing literature has also examined the characteristics of maritime trade during crisis events. For instance, Millefori et al [36] analysed the effects that the COVID-19 pandemic and containment measures had on the shipping industry per type of commercial shipping.

5.2. Contributions

The empirical analyses of historical maritime trade can help forecast future activity — this is particularly helpful during rare crisis events [36]. To scale to large volumes of maritime trade, trajectory reconstruction techniques have been employed and customized [19, 34, 33]. The proposed algorithms maintained only the minimum number of trajectories reflecting current traffic patterns. Moreover, there are techniques that handle routes with missing data and give the best possible estimation from the available input [33]. Finally, cargo type prediction may also help promote data transparency in the maritime industry, because the type of product a vessel carries is typically private information [39].

5.3. Limitations

Several commodities are often handled at the same port (i.e., multi-purpose terminals), or even at the same berth [38]. Moreover, a vessel often transports several commodities. Consequently, estimating the commodities carried by dry bulk carriers with AIS data only has proven difficult [38, 37, 32]. On another issue, matching all the fixtures records to AIS data is not often possible , because not every reported fixture is eventually realized [39].

There are differences from the official customs statistics related to imports and exports in countries whose other transport modes (i.e., pipelines) are important too. Monthly trade statistics are generally available for some countries but not all. Future research could combine AIS data and oil pipeline data to calculate the marine trade volume, and thus improve the accuracy of the oil trade volume calculated with the use of AIS data.

6. Environmental impact

6.1. State-of-the-art

6.1.1. Emissions calculation

Early research estimated the ships' air pollution emissions during different operation modes, i.e., berthing, maneuvering and hotelling [40]. In a similar study, Winther et al [42] calculated the past and future emissions by combining dynamic AIS data with ship engine power functions and technology-stratified emission factors. In a more recent study, Schwarzkopf et al [46] constructed future scenarios about ship emissions based on a virtual shipping fleet. The way of calculating pollutant emissions in the open sea differs from the way of calculating them in ports. Tran et al [49] investigated the container vessel segment by compiling a comprehensive emission profile by vessel size, port call and carriers.

The approaches for emission calculation are often hindered by the absence of some static AIS data, or vessel technical information. To address these issues, Peng et al [45] calculated ship emission inventories based on sampling statistics, using individual vessels with all the necessary data for estimating the population's emissions. In the absence of engine specifications, Zhang et al [44] calculated emissions from vessels through categorical regression based on vessels with similar characteristics. Johansson et al [43] proposed a route generation algorithm to compare emission calculations with previous inventories. They introduced the “most-similar-vessel" to complete the missing ship technical information.

6.1.2. Fuel consumption measurement and savings

Bai et al [58] investigated, for each ship type, the factors that affect the shipowners' choices regarding different feasible schemes for reducing sulfur emissions. Safaei et al [51] suggested a prediction model to estimate fuel consumption based on multiple linear regression. Kim et al [52] used big data techniques to optimize data processing and computing time of the Energy Efficiency Operational Indicator. To estimate fuel consumption, they used static and dynamic AIS data. Watson et al [50] proposed a methodology to estimate the carbon savings by assuming that a ship sails at her lowest observed speed. Stolz et al [54] investigated the time that ships spend at berth by using AIS data, in order to estimate the auxiliary power demand at berth. Sundvor et al [55] investigated route requirements and energy demands of high-speed passenger vessels, aiming to identify the candidates for zero-emission replacement.

6.2. Contributions

The use of AIS data has facilitated emissions and fuel consumption calculation. A noteworthy contribution, in this area, concerns the efforts towards reducing the impact of missing static data, using primarily sampling techniques [45, 59, 43]. Moreover, simplification techniques for dynamic AIS data have been proposed, in order to take advantage of large volumes of data [48].

6.3. Limitations

For the auxiliary engines and boiler, the ship registry database does not always provide the full specifications of installed power; thus, engine usage in various operational modes may not always be calculated [49]. Uncertainty about voyage parameters, such as cruising and maneuvering distance, has also affected the impact of the reported empirical results [41].

For further work, Safaei et al [51] proposed the use of non-linear regression methods, because there is a non-linear relation between speed and fuel consumption. Waves, sea currents and ice cover can increase the required main power; therefore their influence should be examined. Other data sources may also be used for load profiles and distinguishing between loading and unloading at berth, to estimate the distribution of power demand over time [54]. Peng et al [45] suggested examining the uncertainty induced by AIS communication gaps. Finally, there is a plethora of dynamic AIS simplification techniques that may be taken into consideration [60].

7. Summary and Further Work

We have carried out a survey AIS data analytics techniques for shipping business decision-making. Our survey provides a categorization of the areas where AIS data may assist in strategic decision-making, based on the costs that a shipping business needs to cover. Moreover, our survey is useful both as a catalogue of existing research, as well as a critical evaluation of the field. The use of AIS data has facilitated the state-of-practice in shipping business decision-making. Furthermore, enriching AIS data with other data sources is necessary more often than not.

Due to space limitations, we could only present a fragment of our survey here. We chose to focus mostly on the literature of the maritime domain for the benefit of the Data Scientist. We are currently finalizing the complete survey, that presents a detailed discussion of the literature, including work from the fields of Data Science and Artificial Intelligence.

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