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Prediction of vessel arrival time to port: a review of current studies

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ABSTRACT

Accurate prediction of vessel arrival time is crucial for the efficiency of port operations and international trade; however, a systematic review of the research on this topic has not yet been conducted. This paper provides the first systematic review of the prediction of vessel arrival time to port, encompassing 29 academic studies published since 2011. By reviewing the literature, it first identifies and categorizes six key factors affecting vessel arrival time prediction: vessel static information, dynamic information, route conditions, environmental conditions, human factors, and external unexpected factors. The review highlights the challenges of precise vessel arrival time prediction. After closely examining the existing research studies, we found that two frameworks, namely *non-trajectory-based prediction of vessel's ETA to port* and *prediction of vessel's ETA to port by path finding*, and four categories of prediction models are commonly used: statistical models, machine learning models, deep learning models, and reinforcement learning models. This review also explores potential future research directions and serves as a critical resource for feature usage, model selection, the current research state, and future development directions for researchers, industry practitioners, and policymakers, advancing the understanding and application of data-driven prediction methodologies for improved maritime operational efficiency and digitalization.

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Maritime transportation; vessel arrival analysis; estimated time of arrival (ETA); vessel delay prediction; artificial intelligence

1. Introduction

Maritime transportation is an essential component of global trade and commerce, with its efficiency being crucial for ensuring the safety, reliability, and environmental sustainability of shipping operations. Unlike other modes of transportation, maritime shipping boasts the advantages of vast cargo carrying capacity and cost-effectiveness, rendering it the predominant means by which the majority of international trade is conducted. The 2019 report of the United Nations Conference on Trade and Development (UNCTAD 2019b) emphasizes that maritime transport is fundamental to global trade and the international supply chain, with roughly 80% of global cargo being transported by sea-going vessels (UNCTAD 2019a; Wang and Yan 2022; Yan, Wang, and Du 2020). This indispensable mode of transportation not only drives economic growth but also plays a vital role in ensuring the resilience and sustainability of global supply chains in an increasingly

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interconnected world (Elmi et al. 2023; Fratila (Adam) et al. 2021; Li et al. 2023). Due to increased global cargo volumes and vessel sizes (Yap, Lam, and Notteboom 2006), port service demand has exceeded capacity at many ports, resulting in extended vessel waiting times (Golias et al. 2009). These delays lead to increased fuel consumption, emissions (Kaptan 2021), and maritime traffic congestion (Stergiopoulos et al. 2018).

Port operators need accurate vessel arrival times and cargo volumes to better allocate limited port resources (Mekkaoui, Benabbou, and Berrado 2022). While vessels are required to report their estimated time of arrival (ETA) in advance according to IMO regulations (IMO 2006a), accurately obtaining vessel's ETA remains a significant challenge in the maritime industry, as many vessels struggle to precisely forecast their arrival time (Veenstra and Harmelink 2021).

Before the 1990s, maritime researchers and practitioners lack sufficient high-quality tracking data to analyze vessel behavior effectively (Tu et al. 2017). Concurrently, this scarcity posed significant challenges in validating the efficacy of proposed methodologies for predicting vessel's ETA. In response to the demands for enhancing maritime navigation safety and strengthening the regulation of vessel behavior (Zhao et al. 2014), the Automatic Identification System (AIS) was developed in the 1990s to record and report real-time vessel tracking information. In addition, since 2008, onboard AIS transceivers are capable of transmitting AIS data to satellites equipped with AIS receivers, enabling the collection of more comprehensive and higher-quality AIS data for vessels engaged in long-range maritime voyages. According to the IMO regulations, vessels engaged in international voyages exceeding 300 gross tonnages, as well as all passenger ships, must be equipped with an AIS transmitter (IALA 2004). Based on these regulations, substantial real-time AIS data of numerous vessels can be obtained and retained, which typically encompass fields such as AIS identity and location, vessel identity, vessel size, vessel position, sailing speed, navigation direction and status, time stamp, destination (including port name and its ETA), and draught (Yang et al. 2019).

Long-Range Identification and Tracking (LRIT) data (IMO 2006b) is another vessel tracking system alongside AIS. LRIT transmits vessels' GNSS position, timestamp, and equipment identification to designated data centers every 6 h (IMO 2024a). While both AIS and LRIT data can support ETA prediction by tracking vessel movements, AIS data is more commonly used in research (Alessandrini, Mazzarella, and Vespe 2019) due to its comprehensive coverage and accessibility. Despite significant progress in AIS-based ETA prediction since the 2010s, accurate forecasting remains challenging, as will be discussed in Section 7.1.

Although the AIS and LRIT data have significantly advanced research on vessel's ETA prediction, current studies are characterized by inconsistencies in data usage, model selection, and evaluation criteria. To the best of the authors' knowledge, no article has systematically reviewed the existing literature on the problem of vessel's ETA prediction. Consequently, this review aims to fill this gap by conducting a comprehensive review of the existing studies on vessel's ETA to port prediction, including 29 academic studies published since 2011. The rest of this paper is delineated in the following manner: Section 2 elaborates on the methods used to search for and organize the relevant literature in this study. Section 3 outlines the key factors that influence vessel's ETA prediction while providing a detailed analysis that highlights the challenges and difficulties associated with achieving accurate ETA prediction. Section 4 describes and explains the two main frameworks that have been used in existing research on vessel's ETA prediction. Section 5 provides an overview of the specific models applied in the current research. Section 6 discusses potential future research directions and opportunities in vessel's ETA prediction. Section 7 provides conclusions of this paper.

2. Literature review method and structure

Given the emphasis on vessel arrival time to port prediction problem, we have searched the Scopus, Google Scholar, and Web of Science databases using keywords related to vessel's ETA prediction, such as 'ship estimated time of arrival,' 'ship ETA prediction,' 'ship delay prediction,' 'vessel arrival punctuality,' 'ship arrival time prediction' and 'vessel arrival time prediction.' The keywords for paper selection are initially derived from a combination of commonly used terms in vessel's ETA prediction studies and prior knowledge of the field. After identifying an initial set of vessel arrival time prediction studies, we expanded our search scope by incorporating their keywords into our search pool to discover additional relevant research.

The initial search yields a total of 826 results. As the first step, we conduct a preliminary screening based on the titles and keywords of the articles to remove those that are clearly unrelated to the prediction of vessel arrival time to port. Following this, we further examine the abstracts and conclusions of the articles to assess their relevance to our research focus. After the screening process, the pool of articles is reduced to 62. Subsequently, we review the experimental results sections of these 62 papers to assess their relevance and alignment with the focus of this study. To ensure the comprehensiveness of our review, we supplement this selection with backward and forward citation analysis, which involves a thorough review of both their cited references and the works that have cited them. Given the specific focus of this review on predicting the vessel's ETA at port, we apply additional inclusion and exclusion criteria. Specifically, we exclude studies that primarily address port resource allocation based on given vessel arrival patterns or those solely dedicated to vessel trajectory prediction while without ETA prediction, as their objectives diverge from the primary aim of estimating vessel's ETA to the port. These steps ensured the relevance and rigor of the selected studies.

Furthermore, we encounter two key challenges during the literature search process. First, relevant studies are dispersed across a diverse range of journals and conferences, which makes it difficult to comprehensively identify all pertinent literature. Second, some studies have misleading titles that suggest a focus on vessel arrival time prediction but primarily address related yet distinct topics, such as port resource scheduling under specific vessel arrival patterns. These challenges highlight the importance of careful screening and detailed evaluation to ensure the inclusion of only the most relevant research in this review.

Finally, we identify 29 related papers and classify them into two frameworks, namely *Non-trajectory-based prediction of vessel's ETA to port* and *prediction of vessel's ETA to port by path finding*, which are illustrated with more details in Section 4. We also categorize the specific models employed in existing studies into four types: statistical models, machine learning models, deep learning models, and reinforcement learning models. A detailed discussion of these categories will be provided in Section 5. An analysis of the publication years of the papers is conducted in terms of their prediction models employed, and the results are demonstrated in Figure 1. The publication venues and the distribution of papers published that are covered in this review are shown in Figure 2.

Figure 1 demonstrates a notable upward trend in the number of publications on vessel arrival time to port prediction from 2017 to 2022. Among the four categories of models analyzed, machine learning methods have consistently been the most widely adopted approach, reflecting their versatility and performance in this domain. Deep learning models, while initially less prevalent, have shown a sharp increase in adoption from 2018 onward, likely driven by advancements in computational power and the availability of large datasets. Statistical learning models have maintained a steady presence throughout the observed period. While these approaches have not experienced significant fluctuations in popularity, the continued usage highlights their value in certain predictive scenarios. It is also worth noting that only one study (K. Park, Sim, and Bae 2021) has employed reinforcement learning for vessel's ETA prediction, indicating that this technique is still in its nascent stage within this field.

3. Key factors influencing vessel's ETA to port prediction

Predicting vessel's ETA is a complex task that is influenced by various key factors. This section aims to provide a thorough overview of these critical factors and explain the reasons of the difficulties in accurate vessel's ETA prediction. Those key factors include vessel static information, dynamic

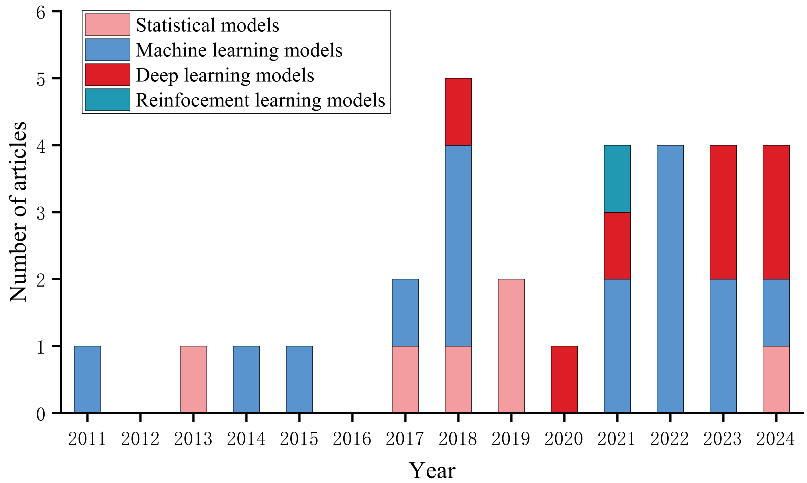


Figure 1. Summary of the reviewed papers by year and prediction method.

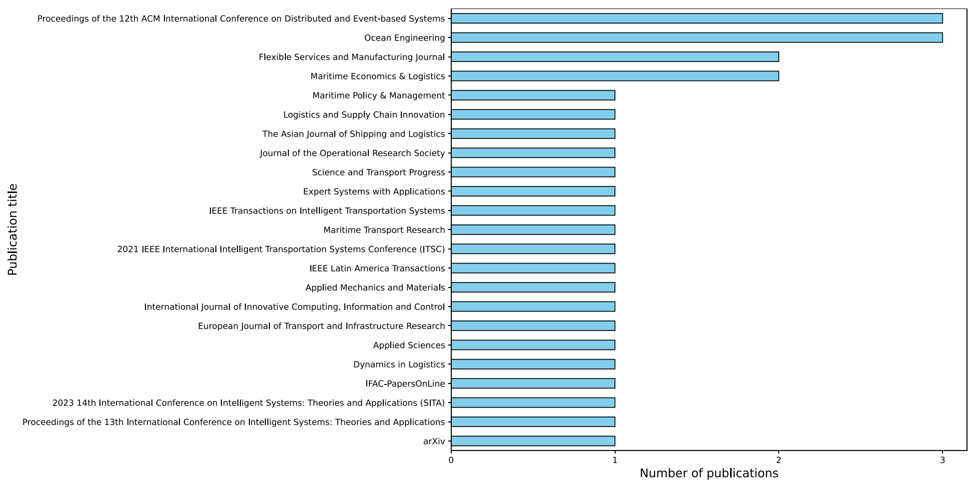


Figure 2. Distribution of publications by venue.

information, route conditions, environmental conditions, human factors, and external unexpected factors. To identify the key factors affecting vessel's ETA prediction, we conduct an extensive literature review and gather insights from industry professionals. Our selection process focused on factors that have been shown to impact vessel arrivals in both theoretical studies and practical operations.

The first group of factors consists of those widely considered in existing research, including vessel-related information, route conditions, and environmental conditions. Vessel-related information encompasses both static factors, such as ship type, length, and draft, which determine navigational constraints, and dynamic factors, such as speed and course, which reflect real-time operational adjustments. Route conditions, including maritime traffic density, navigational restrictions, and port accessibility, directly influence voyage efficiency and potential delays. Environmental conditions, such as wind, waves, currents, and adverse weather, further impact vessel speed and routing, making them essential considerations in ETA prediction models.

The second group includes factors that are rarely addressed in existing studies but have been highlighted as important through discussions with industry professionals: human factors and external unexpected factors. Human factors, such as operational decisions made by ship crews and port instructions, can significantly affect vessel arrival time. Decisions related to speed adjustments, fuel efficiency strategies, or risk management are often overlooked in predictive models. External unexpected factors, such as mechanical failures, geopolitical disruptions, and port strikes, introduce additional uncertainty that traditional models often fail to capture. Although these factors are harder to quantify, industry insights suggest that they can have a substantial impact on vessel arrival time prediction.

In the following subsections, we will provide a detailed overview of the specific information contained within each key factor and analyze their impact on vessel's ETA prediction.

3.1. Vessel static information

Vessel static information encompasses attributes that remain relatively constant over a given voyage. These attributes typically include the vessel's type and size, age and management level, technical specifications and historical voyage data, which will be elaborated on in the following subsections.

3.1.1. Vessel type and size

Common vessel types in international trade include container ships, bulk carriers, tankers, general cargo ships, passenger ships, multipurpose vessels, and Liquefied Natural Gas (LNG) carriers (IMO 2024b). Container ships are commonly used in long-distance oceanic voyages and typically stop at multiple intermediate ports to load and unload cargo. With the operational facilities and standardized procedures implemented at ports (Yap, Lam, and Notteboom 2006), container ships exhibit a high degree of efficiency in cargo handling operations, leading to relatively stable and predictable port stay periods. Unlike container ships, the loading and discharging processes for bulk carriers and general cargo vessels are highly dependent on the type of cargo and the port's facilities (Hvattum, Fagerholt, and Armentano 2009). Their cargo handling rates and port stay duration are more uncertain and difficult to predict, substantially impacting the accuracy of ETA prediction. Certain specialized vessel types, such as LNG carriers and refrigerated vessels, necessitate the maintenance of consistent speeds and navigational courses to ensure cargo safety (Vanem et al. 2008). This requirement for speed and course stability directly influences the prediction of vessel's ETA at designated ports. Unlike other vessel types, passenger ships exhibit a unique characteristic where the occupancy rate influences the vessel's overall fuel consumption rate (Dujmović et al. 2022) and sailing speed, consequently impacting the accuracy of ETA prediction.

Vessel size is characterized by its physical dimensions such as vessel length, beam, height, and draught, as well as its volume and weight capacities indicated by gross tonnage (GT) and deadweight tonnage (DWT), respectively. Vessel size directly impacts vessel's operational efficiency during navigation and port operations (Pietrzykowski and Wielgosz 2021), thereby exerting an impact on vessel's ETA prediction. The impact manifests itself principally in two aspects. First, when vessels navigate relatively confined waterways such as canals, rivers, and certain congested channels, larger vessels face increased constraints necessitating more conservative navigational strategies. Simultaneously, they are more susceptible to limitations imposed by maximum traffic flow capacity (Elsherbiny et al. 2020), resulting in prolonged waiting time. Second, upon awaiting entry into ports, the availability of berths capable of accommodating larger vessels with deeper drafts is typically more restricted. Consequently, these vessels encounter extended and less predictable waiting periods, rendering their ETA more difficult to predict. GT and DWT significantly influence the accuracy of vessel's ETA prediction, primarily through their impact on cargo handling duration at intermediate ports. Furthermore, GT and DWT typically correlate with a vessel's draught, collectively affecting berth availability at destination ports, given the heterogeneous nature of port infrastructure, where berths are characterized by varying water depths (MPA 2024).

3.1.2. Vessel age and management level

Vessel age refers to the period in year since the vessel is originally built and launched and plays a critical role in determining its operational efficiency and reliability (Fan, Wang, and Yin 2019). Older vessels are prone to higher frequencies of mechanical failures due to their cumulative wear and tear, which can result in unexpected interruptions or the necessity for additional repairs during voyages, subsequently causing delays. Furthermore, older vessels often exhibit reduced sailing speeds and diminished fuel efficiency, which not only prolongs travel time but also necessitates more frequent refueling stops, further impacting the prediction of their ETA.

The management level of a vessel can also influence its ETA prediction accuracy. Vessels under superior management, as reflected by their flag states and operating companies, tend to exhibit better support practices because both entities are responsible for the vessel's operations, maintenance, and assessment. Consequently, vessels managed by high-performing flags or companies typically experience fewer deficiencies on average, as these management parties are more experienced in ship management (Yan and Wang 2019). Well-maintained vessels are less susceptible to mechanical issues or structural defects that could lead to unexpected breakdowns or repairs at sea, events that would significantly disrupt their scheduled voyages. Such vessels often demonstrate higher fuel efficiency, a direct result of proper maintenance routines that keep engines, propulsion systems, and hull surfaces in optimal condition (Barreiro, Zaragoza, and Diaz-Casas 2022). This enhanced efficiency allows vessels to keep more stable speeds and better follow their planned routes, thereby improving their ETA prediction accuracy.

3.1.3. Technical specifications

Technical specifications generally refer to the vessel's main engine power output and the sophistication of the propulsion system. Vessels equipped with higher-powered engines and advanced propulsion technologies, such as contra-rotating propellers or pod propulsion systems, can theoretically achieve greater sailing speed. This enhanced speed could significantly reduce the transit time, consequently yielding earlier ETA prediction. Another factor is the vessel's maneuvering performance, encompassing its acceleration, deceleration, and turning agility. These attributes influence a vessel's overall navigation strategy, particularly in constrained waterways and congested maritime zones (Ince and Topuz 2004). These maneuvering attributes collectively shape a vessel's navigational flexibility, allowing it to adapt its trajectory and speed in response to situational demands. In essence, vessels with superior maneuvering performance navigate with more consistent speeds, shorter transit time through complex areas, and fewer speed-sapping course changes (Pietrzykowski 2008), resulting in an earlier prediction of their ETA. Consequently, when forecasting vessel's ETA, it is important to consider not just a vessel's straight-line speed potential but also its dynamic maneuverability.

3.1.4. Historical voyage data

Vessel historical voyage data generally refer to the vessel tracking data of analogous vessels on identical routes among which historical average travel time stands out as the most critical metric in vessel's ETA prediction. This information serves as a robust prior, grounding the prediction of vessel's ETA in empirical evidence. Vessels within a class typically share similar design and performance characteristics, so they often exhibit remarkably consistent behavior on the same routes. The historical average travel time, derived from the voyages of numerous vessels, substantially mitigates the impact of stochastic factors. However, the utility of historical voyage data must be evaluated in terms of its timeliness and relevance. If there are significant changes in the navigational routes, such as canal expansions or blockages, the reference value of historical data can rapidly diminish. A salient example is the 2016 expansion of the Panama Canal (PC), which, following upgrades to its lock system, significantly increased the size of vessels capable of transiting through the PC. This infrastructural enhancement led to a significant shift in the dynamics of the maritime network, with the prominence of U.S. west coast ports declining, while East Coast and Gulf ports experienced an increase in their cargo market share (Liu, Wilson, and Luo 2016; C. Park, Richardson, and Park 2020). These transformations significantly influence the cargo throughput of affected ports, thereby altering traffic volumes along established shipping routes. Consequently, when predicting the ETA for vessels transiting the PC, it is critical to exercise caution when utilizing data predating 2016, as it may not accurately reflect current maritime traffic patterns and transit time.

3.2. Vessel dynamic information

Vessel dynamic information, particularly concerning a vessel's operational status, is critical for accurate ETA prediction. This operational status includes real-time data on the vessel's current speed and heading, engine performance, fuel consumption rates, and the specific operational adjustments made by the crew. The dynamic nature of these variables necessitates continuous monitoring and integration into predictive models, as they can fluctuate due to navigational decisions, mechanical conditions, and unforeseen incidents during the voyage. Vessel dynamic information is typically conveyed through AIS data, with its fields generally structured as shown in Table 1. The vast majority of contemporary research on vessel's ETA prediction utilizes AIS data to obtain vessel dynamic information. This methodology facilitates a detailed analysis of a vessel's operational behavior during specific voyages (Duan et al. 2024; Xiao et al. 2015), encompassing traversed regions (P. Chen et al. 2024), speed variations (Xie et al. 2023), precise navigational routes (Lee and Kim 2024), visited ports (Xin et al. 2024), etc. Once processed, these data serve as critical features for estimating the remaining travel time. Variations in vessel speed, induced by changes in external conditions or adjustments for fuel optimization, directly influence transit time and, consequently, the ETA. Similarly, alterations in heading to avoid obstacles or adverse weather conditions impact the ETA prediction. Real-time monitoring of engine performance and fuel consumption rate provides critical data for making informed decisions regarding speed and route adjustments, thereby improving the accuracy of ETA prediction.

3.3. Route conditions

Route conditions are pivotal in the accurate prediction of a vessel's ETA prediction, encompassing various factors such as traffic congestion and navigational channels, including territorial waters, regulated zones, inland waterways, canals, and straits. Each of these elements imposes specific constraints and potential delays that can possibly be incorporated into ETA prediction models. Vessels often traverse narrow or shallow channels where speed restrictions are imposed to ensure safe navigation (Pietrzykowski 2008). These channels may require precise maneuvering and adherence to strict navigational protocols, which can slow down transit time. For example, in constrained channels like the Kiel Canal, speed limits and the need for precise

Table 1. AIS dynamic vessel information fields.

Field Name	Type	Description
Vessel position	Float	Latitude and longitude (up to 10^{-4} accuracy)
Speed over groud (SOG)	Float	Vessel speed over ground (knots)
Course over ground (COG)	Float	Vessel course over ground (knots)
Heading	Integer	Vessel true heading (degrees)
Rate of turn	Float	Right or left (ranging from 0 to 720° per minute)
Navigation status	String	Including "at anchor," "under way using engine(s)," and "not under command"
Time stamp	UTC timestamp	The precise time at which a particular AIS message is generated or received

navigation can significantly affect overall voyage duration. When entering territorial waters, vessels must comply with local maritime regulations (Cariou and Cheaitou 2012), including speed limits, designated shipping lanes, and sometimes compulsory pilotage. Such regulations are designed to ensure safety and environmental protection but can also introduce delays. For instance, vessels entering the United States' territorial waters often face stringent regulations that can slow down their progress and impact their arrival time to port. High traffic density in busy shipping lanes or major ports can lead to queuing time and waiting time (Yeo, Roe, and Soak 2007). Congested areas such as the port of Shanghai or the Singapore Strait often experience significant traffic volume, leading to delays in docking, loading, and unloading. This congestion can cause substantial deviations from ETA prediction, especially during peak periods. In addition, transit through inland waterways and canals, such as the Panama Canal, which has been discussed in Section 3.1.4, is subject to additional constraints, including lock operations and scheduling slots for transit.

3.4. Environmental conditions

Environmental conditions can significantly affect the accurate prediction of a vessel's ETA. These conditions encompass a range of factors, including weather data, sea state information, and potential natural disasters. Understanding and integrating these elements into predictive models are essential for improving the reliability of ETA prediction.

Weather conditions, such as wind speed and direction, precipitation, visibility, and atmospheric pressure, have a moderate impact on a vessel's navigation and speed. Adverse weather conditions, including storms, heavy rain, fog, and high winds, can necessitate changes in course, reductions in speed, or even temporary suspension of voyage operations (Bitner-Gregerse, Soares, and Vantorre 2016). For instance, gale-force winds can hinder a vessel's progress by increasing resistance and making navigation more challenging. Similarly, reduced visibility due to fog or heavy rain can slow down operations, particularly when entering or leaving ports. In the current research, Pani et al. (2015) consider wind speed and sea wave as features in machine learning models including logistic regression (LR), decision tree (DT), and random forest (RF), and point out that weather-related predictors, when measured at a point equidistant (12 h) from Cagliari port, yield superior model performance. SubsequentlyJahn and Scheidweiler (2018) use a neural network model considering weather conditions as features to analyze complex maritime traffic patterns in the German North and Baltic Sea, enabling accurate prediction of future vessel locations and, notably, precise estimations of vessel arrival time. More recently, El Mekkaoui, Benabbou, and Berrado (2023) and Abdi and Amrit (2024) incorporate weather data as features and utilize deep learning models to predict vessel's ETA, demonstrating the contribution of weather data within sequential models to the accuracy of ETA prediction.

Sea state information, including wave height, wave direction, swell, and current patterns, also profoundly impacts a vessel's ETA. High waves and swell can reduce a vessel's speed and increase fuel consumption as the vessel must navigate through more turbulent waters. Currents can either aid or hinder a vessel's progress depending on their direction and strength. For example, a favorable current can speed up a vessel's journey, while a strong opposing current can significantly slow it down. Therefore, incorporating real-time sea state data into ETA prediction models is essential for adjusting transit time accurately; however, the utilization of sea state data in existing research remains relatively limited.

Natural disasters, such as hurricanes, typhoons, tsunamis, and earthquakes, can cause severe disruptions to maritime operations (Verschuur, Koks, and Hall 2020) and significantly affect ETA. These events can lead to rerouting, delays, or even port closures. For example, hurricanes and typhoons bring with them extreme winds and heavy seas that can force vessels to take longer, safer routes or seek shelter, thus delaying their arrival. Tsunamis can cause sudden and unpredictable changes in sea level, making certain routes impassable and necessitating significant adjustments to voyage plans. Earthquakes, particularly those that affect port infrastructure, can lead to extended delays in loading and unloading cargo, further impacting ETA.

3.5. Human factors

Human factors play a critical role in the accurate prediction of a vessel's ETA. Key elements in this context include the crew, speed strategy, and port instructions. These human elements influence operational decisions and execution, thereby impacting the overall voyage time and ETA.

The competence and experience of the crew are fundamental to effective vessel operations and ETA accuracy. An important aspect is crew behavior that significantly impacts the likelihood of errors occurring during routine navigation, and such impacts are typically related to the training they have received and the extent of their experience. Experienced crew members are adept at handling navigational challenges, performing efficient maintenance, and responding promptly to unexpected situations. Their ability to make quick and informed decisions can mitigate delays caused by mechanical failures or adverse conditions (Stevens and Parsons 2002). Conversely, a less experienced or poorly coordinated crew might struggle with these tasks, leading to inefficiencies and increased voyage time. Therefore, crew training, experience, and coordination are pivotal in maintaining operational efficiency and adhering to predicted vessel's ETA.

Individual crew members' personal habits, such as their work routines, attention to detail, and adherence to safety protocols, can also play a role in vessel's ETA prediction accuracy. Habits that promote vigilance and efficiency, for instance, contribute to timely operations, while those that foster complacency may lead to delays. Furthermore, occasional judgment errors, which can arise from overconfidence, miscommunication, or a misunderstanding of environmental conditions, are another factor that can affect navigational efficiency. The physical and psychological condition of the crew also has a critical impact on operational outcomes. Fatigue, stress, and poor health impair decision-making, slow reaction time, and reduce overall performance, increasing the risk of navigational errors and unforeseen delays. Thus, maintaining the crew's well-being through adequate rest, health management, and stress reduction is vital to minimizing such risks. Psychological factors, including crew morale and team cohesion, are equally important, as well-coordinated and motivated crews are more likely to operate efficiently and respond effectively to challenges. Therefore, crew training, experience, personal habits, and physical and psychological well-being contribute to operational efficiency and the accuracy of vessel's ETA prediction.

The speed strategy adopted by the vessel's captain and crew is another significant factor affecting ETA. Speed decisions are influenced by fuel efficiency considerations, weather conditions, and navigational constraints. An optimal speed strategy balances the need for timely arrival with fuel consumption and safety. For instance, in calm seas and favorable weather, maintaining higher speeds can ensure timely arrivals. However, in rough seas or adverse weather conditions, reducing speed might be necessary to ensure safety, even if it means extending the voyage duration. Additionally, economic considerations, such as fuel prices, can impact speed strategy decisions, with higher fuel costs potentially leading to slower, more fuel-efficient speeds. Based on a dataset encompassing information on 352 container ship arrivals over a 9-month period at seven terminals within three North American ports, Hasheminia and Jiang (2017) indicate that the strategies vessels adopt following disruptions depend on fuel prices and the congestion levels at the destination ports. When the destination port is already congested, container ships are likely to experience longer waiting time, resulting in higher delay costs, and thus, vessels are more inclined to increase their speed to mitigate delays.

Port instructions, including docking schedules, berth availability, and pilotage requirements, significantly influence vessel's ETA prediction. When the port is relatively busy and there are few berths remaining, port operators typically notify incoming vessels to reduce their speed for a certain period to avoid unnecessary berthing delays. Efficient communication and coordination with port authorities ensure that the vessel can dock promptly upon arrival, minimizing waiting time.

Therefore, acquiring knowledge of the instructions issued by port operators to incoming vessels can improve the accuracy of ETA prediction.

3.6. External unexpected factors

External unexpected factors can significantly impact the accuracy of a vessel's ETA prediction. These unexpected factors include warfare, piracy, and detention, each posing unique challenges that can lead to substantial delays and unpredictability in maritime navigation. Additionally, accidents and incidents that occur as a vessel approaches port, as well as customs declarations and inspections, can further contribute to delays.

Warfare poses a significant threat to maritime operations, potentially leading to drastic deviations from planned routes and schedules. In regions affected by conflict, vessels may need to take longer, alternative routes to ensure safety, thereby extending voyage time (Stanivuk, Lalić, and Amižić 2023). Additionally, the threat of military actions can result in port closures or restricted access to critical maritime corridors, further complicating navigation and scheduling. The need for enhanced security measures and the potential for unexpected disruptions necessitate constant monitoring and dynamic adjustment of voyage plans, significantly impacting ETA predictions.

Piracy remains a considerable concern in several key maritime regions, such as the Gulf of Aden, the Strait of Malacca, and parts of West Africa. The threat of piracy necessitates heightened vigilance and often requires vessels to adopt specific anti-piracy measures (Gong, Jiang, and Yang 2023), such as rerouting through safer but longer passages or traveling in convoys with naval escorts. These measures can lead to increased transit time and variability in arrival schedules. Additionally, if a vessel is attacked or hijacked, the resultant delay can be extensive, severely affecting the predicted ETA. The cost of implementing security measures and the potential for ransom negotiations further complicate the predictability of arrival time.

Detention refers to the potential for vessels to be detained by authorities due to regulatory, legal, or compliance issues. This can occur due to a variety of reasons, including non-compliance with environmental regulations, safety standards, or customs and immigration laws. Detentions can happen at any point in the voyage, often unexpectedly, and can lead to significant delays. For instance, a vessel failing to meet the IMO regulations on emissions might be detained and can proceed to sea after the deficiencies are rectified (Y. Chen et al. 2022). Similarly, legal disputes or inspections can result in prolonged port stays, disrupting the planned schedule and impacting ETA prediction.

Accidents and incidents that occur as a vessel approaches port can have severe consequences on the accuracy of ETA predictions. Such events include collisions, groundings, or mechanical failures, which not only require immediate response and possible assistance from nearby vessels or port authorities but also may result in significant delays (Chang and Park 2019). The consequences of an accident, such as investigations or repairs, can further prolong the vessel's stay, leading to deviations from the intended schedule. Incidents such as hazardous cargo spills or onboard fires introduce additional complexities, as they often necessitate extensive safety measures, environmental assessments, or even temporary port closures, all of which contribute to substantial unpredictability in maritime operations. Customs declarations and inspections represent another source of delay, particularly in ports where regulatory scrutiny is heightened. Before docking, vessels are required to submit various declarations related to cargo, crew, and health status (Salihoglu and Bal Beşikçi 2022). If discrepancies arise in the documentation or customs officials decide to conduct a thorough inspection, the vessel may experience extended waiting time, thus influencing the prediction of vessel arrival time to the next port.

Based on the above discussions, we summarize the potential features corresponding to each factors that can be incorporated into prediction models in Table 2 and compile the targeted vessel type, the influencing factors considered, and the data sources used in the current academic

Table 2. Potential features for vessel's ETA prediction.

Factor	Potential features
Vessel static information	Vessel type, vessel length, vessel beam, vessel height, vessel gross tonnage, vessel dead-weight tonnage, vessel age, vessel flag state, vessel operations company, vessel engine power rate, vessel speed change rate, vessel turning radius, historical voyage travel time
Vessel dynamic information	Vessel position, vessel speed over ground, vessel heading, vessel course over ground, vessel fuel consumption rate, vessel navigation status, vessel rate of return, vessel engine revolutions per minute (RPM), engine temperature, vessel engine power output
Route conditions	Vessel traffic density, regional speed limit, regional emission limit, water depth, canal width, canal length
Environmental conditions	Wind speed, wind direction, precipitation, visibility, atmospheric pressure, sea wave height, sea wave direction, swell, sea current, storm, heavy rain, fog, high wind, hurricanes, typhoons, tsunamis, earthquakes
Human factors	Number of violations, decision-making speed, response time to alarms, experience and skill level, crew punctuality, crew health and fitness level, maintenance level and frequency, vessel speed strategy, port instruction type
External unexpected factors	Regional war risk, regional piracy risk, detention risk, accidents and incidents risk, custom declarations and inspections

literature on vessel's ETA prediction, as shown in Table 3. To further facilitate a more intuitive understanding for readers, we visually represent these influencing factors in Figure 3.

4. Prediction frameworks

Based on existing research on vessel's ETA prediction, we classify ETA prediction frameworks into two categories. One is non-trajectory-based ETA prediction, which directly uses existing information including vessel static information, historical travel time, AIS data, environmental conditions, and other data sources as features for prediction. This framework is named *framework 1*, which typically relies on statistical techniques, machine learning, or deep learning algorithms to establish a direct mapping between the input features and the arrival time, and solely concentrates on advancements in vessel's ETA prediction performance. The other is trajectory-based ETA prediction, namely *framework 2*, which first forecasts the vessel's future path to destination and then estimates the remaining travel time based on the predicted path. *Framework 2* advances maritime research by integrating vessel's ETA prediction with critical domain-specific challenges, including voyage destination prediction, regional navigation safety assessment, and just-in-time (JIT) system optimization.

The vessel's ETA to port is subsequently determined by adding the predicted remaining travel time to the current time. In the following subsections, we will delve into these two frameworks in more details and explain the general procedures of these two frameworks.

4.1. Framework 1: non-trajectory-based prediction of vessel's ETA to port

Since 2011, the majority of vessel's ETA prediction frameworks have predominantly utilized *framework 1* based on existing data rather than trajectory-based prediction. This framework is typically more adaptable for long-distance and long-duration ETA prediction as less voyage data is needed. The overall framework of direct prediction of remaining travel time is represented in Figure 4. Within this framework, researchers systematically organize various information sources needed for vessel's ETA prediction. These sources typically encompass the major categories of factors discussed in Section 3, and data from these sources are combined in a unified dataset. The subsequent phase involves data preprocessing, which includes data cleaning, transformation, and feature construction. Following the extraction of the critical features, which are derived from the six data sources introduced in Section 3, current research typically employs artificial intelligence (AI) models for training and evaluation. In these models, the extracted features serve as inputs, while the output is the remaining travel time to port,

Table 3. Summary of existing literature on vessel type, data source description, and considered factors in ETA prediction problem.

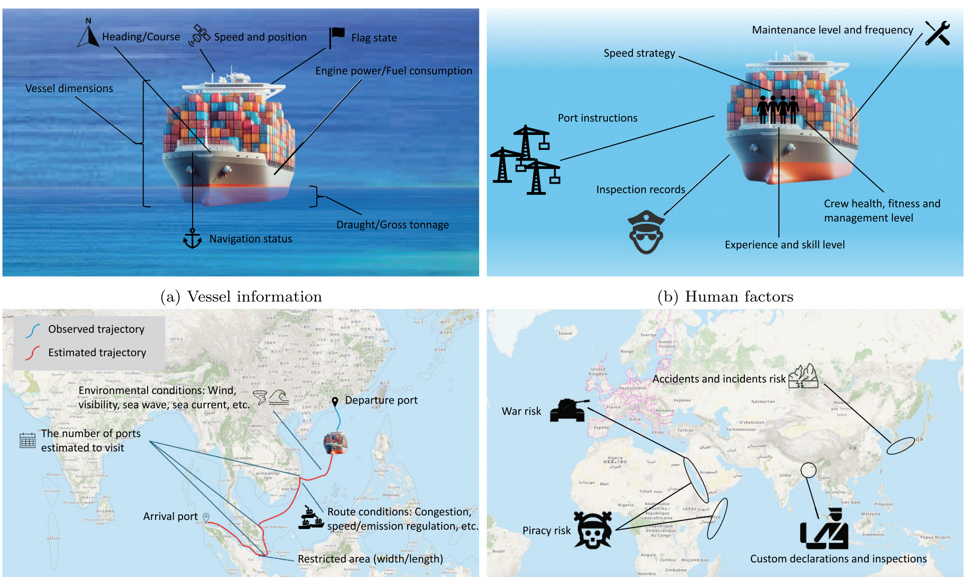
	Vessel type	Data source description	Factors considered					
Literature			1	2	3	4	5	6
Fancello et al. (2011)	Container ships	N.A.	√	√				
Du et al. (2013)	Container ships	Vessel arrival data at container ports including Ningbo, Guangzhou, Yantai, etc.	√	√				
Pani et al. (2015)	N.A.	Data collected at the Antwerp port and weather conditions	√	√		√	√	
Kim, Kim, and Park (2017)	N.A.	184,083 cases based on distinct bills of lading (BoLs) containing 85 variables from Jan 2012 to Apr 2014	√	√				
Salleh et al. (2017)	Container ships	Two container vessels' port call information	√	√				
Jung et al. (2018)	N.A.	N.A.	√	√				
Jahn and Scheidweiler (2018)	N.A.	Historical AIS and environmental data of the year 2016 in German North and Baltic Sea	√	√				
Bodunov et al. (2018)	N.A.	Spatio-temporal data including 300 vessels and 300,000 entries	√	√				
Yu et al. (2018)	Container ships	AIS data on vessel arrivals from 1 June 2008 to 31 May 2009, including 2066 container ships arriving at Ningbo container terminal	√	√				
Nguyen, Le Van, and Ali (2018)	6 types, including cargo vessels, tugs and oil tankers, etc.	AIS data for GC has a total of 200,315 samples from 350 voyages of 168 vessels from 10 March 2015 to 19 May 2015 in the Mediterranean Sea provided by BigDataOcean	√	√				
Alessandrini et al. (2019)	N.A.	AIS data and LRIT data from Trieste, an Italian city in the northeast Adriatic Sea	√	√				
Onyshchenko and Koskina (2019)	Cargo ships	N.A.	√					
El Mekkaoui, Benabbou, and Berrado (2020)	N.A.	AIS data for one vessel going from Ceuta to Gemlik, the number of instances is 1985	√	√				
Kwun and Bae (2021)	N.A.	N.A.	√	√		√		
K. Park, Sim, and Bae (2021)	N.A.	AIS data near the port of Busan, including 1,500 vessels	√	√				
Ogura, Inoue, and Uchihira (2021)	N.A.	Historical operating data of vessels transporting appliances cargoes between Japan and Taiwan	√	√		√		
Veenstra and Harmelink (2021)	N.A.	Individual vessel arrival data for the year 2019, including 6909 port calls of vessels from Dutch startup company Teqplay	√	√				
Noman et al. (2021)	Container ships	AIS data for the Bremerhaven to Minden section of the Inland Weser River Waterway and the Minden to Brunswick section of the Inland Mitland Canal waterway, with a total of 16,103,910 data pieces of 2,395 container ships	√	√			√	
Mekkaoui, Benabbou, and Berrado (2022)	15 types of vessels	180,000 rows of AIS data in the Mediterranean Sea for the period from April 1 to 28 April 2015	√	√				
Valero et al. (2022)	Container ships	3,761,994 AIS messages for 6,618 container ships	√	√				
Xu et al. (2022)	Tankers	Historical AIS data provided by the Danish Maritime Authority (DMA) including data on tankers heading to Skarn Port in Danish waters	√	√				

(*Continued*)

Table 3. (Continued).

Literature	Vessel type	Data source description	Factors considered 1	2	3	4	5	6
Bourzak et al. (2023)	Tugs, barges and merchant vessels	Data including a total of 84,045 observations, representing 38,930 distinct trips made by 1,030 different vessels, including 26 distinct types	√	√				
El Mekkaoui, Benabbou, and Berrado (2023)	Bulk ships	AIS data from FleetMon, vessel particulars from shipping company, weather information, and vessel arrivals to the port of Jorf Lasfar from 1 January 2019 to 31 December 2020	√	√		√		
Chu, Yan, and Wang (2024)	14 types of vessels	ETA and actual time of arrival (ATA) data from Marine Department of Hong Kong	√					
Kolley et al. (2023)	General cargo vessels	AIS data for the Port of Miami from 2018 to 2020 provided by the National Oceanic and Atmospheric Administration (NOAA)	√	√				
Abdi and Amrit (2024)	Container ships and tankers	AIS data and relevant environmental information in Europe	√	√		√		
Lei et al. (2024)	Multiple types	1,171,443 AIS records of vessels on the eastern reaches of the Yangtze River	√	√	√			
Zhang et al. (2023)	N.A.	AIS data from the Singapore Strait, pilotage booking information, and meteorological data for the period from 1 January 2018, to 31 December 2018	√	√		√	√	
Guan, Cao, and Cheng (2024)	Cargo ships and tankers	AIS data	√	√				

1: Vessel static information; 2: Vessel dynamic information; 3: Route conditions; 4: Environmental conditions; 5: Human factors; 6: External unexpected factors



(a) Vessel information (b) Human factors

(c) Route and environmental conditions (d) External risk conditions

Figure 3. Visualization of influencing factors in vessel's ETA prediction.

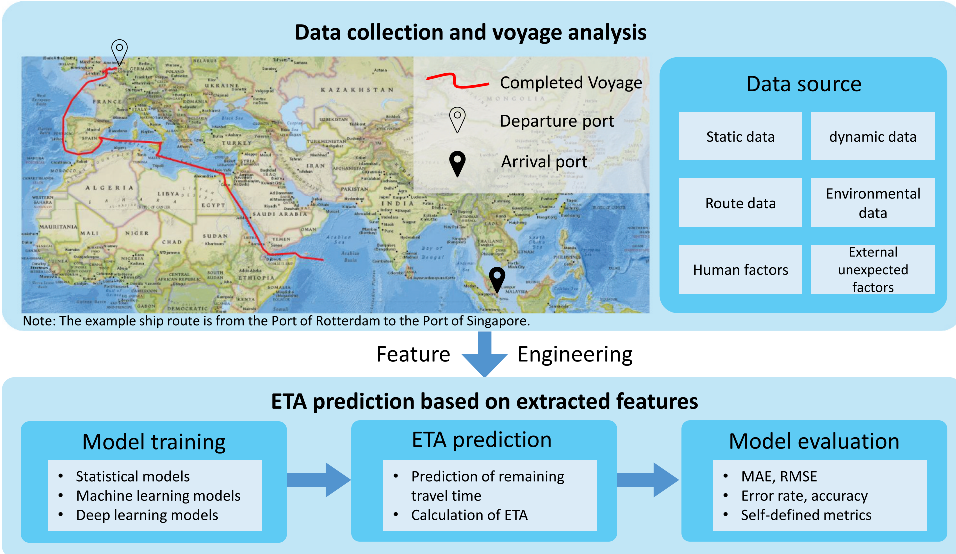


Figure 4. An overview of framework 1: non-trajectory-based prediction of vessel's ETA to port.

which is subsequently converted into the ETA to port. The typical prediction models will be presented in Section 5. Upon the completion of the training process, these models can then generate reasonable ETA predictions for the vessel by utilizing more up-to-date information including AIS data, weather forecast data, and other relevant inputs.

4.2. Framework 2: prediction of vessel's ETA to port by path finding

As research on vessel's ETA prediction continues to advance, some researchers have employed an alternative framework based on trajectory-based prediction since 2019 (Alessandrini, Mazzarella, and Vespe 2019) as illustrated in Figure 5. This framework first forecasts the remaining trajectory of the vessel's voyage using various existing information sources, such as vessel AIS data and route conditions, and then estimates the vessel's average sailing speed or travel time along this predicted trajectory. The rationale behind this framework is that by forecasting a more accurate and realistic trajectory that aligns with the vessel's navigation strategy, the remaining voyage distance can be approximated more closely to the true value, thus yielding a more precise estimate of the remaining travel time. In addition, when ETA predictions are based on a predicted trajectory, the model can better integrate and leverage external data sources such as environmental conditions, navigational routes, and traffic density. By incorporating such data, the model can account for factors that significantly influence sailing conditions and speeds, thereby enhancing the accuracy of ETA predictions. This trajectory-based approach not only allows for a more granular understanding of the vessel's future route but also facilitates the inclusion of dynamic elements that may affect the voyage, such as weather patterns and maritime traffic.

Compared to the framework introduced in Section 4.1, which directly predicts ETA using existing information as features, existing research based on trajectory prediction tends to focus on short-term ETA predictions. The average prediction error in these studies is typically within a few hours. In contrast, the framework discussed inSection 4.1 is more broadly applicable, with a wider range of average prediction errors. It is important to recognize that neither framework is inherently superior to the other. The selection of an appropriate framework should be determined by the specific prediction scenario and the availability of data sources.

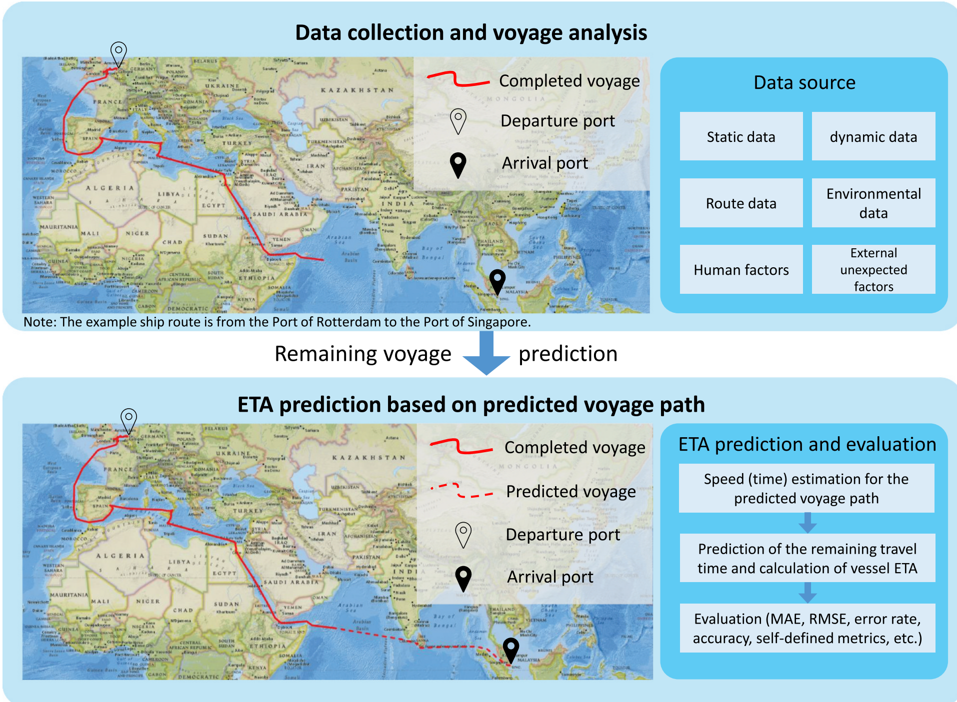


Figure 5. An overview of framework 2: prediction of vessel's ETA to port by path finding.

5. Vessel's ETA to port prediction models

The prediction of vessel's ETA to port is a critical undertaking with significant implications for various maritime operations and supply chain logistics. Over the years, researchers have developed and employed a diverse array of modeling approaches to tackling this intricate problem. In this section, we provide a comprehensive overview of the predominant models that are employed for vessel's ETA prediction, encompassing statistical models, machine learning models, deep learning models, and reinforcement learning models.

5.1. Statistical models

Statistical models typically rely on the historical voyages or port visit data to fit vessel transit time or sailing speeds to certain statistical distributions, which is utilized in both *framework 1* and *framework 2*.

Du et al. (2013) employ the chi-square test to perform a statistical analysis on the arrival data of vessels at several container terminals in China. The analysis focuses on two aspects: the number of vessel arrivals on a daily basis and the inter-arrival time between consecutive arriving vessels. The inter-arrival times are found to follow both exponential and gamma distributions. By utilizing the actual arrival time of the most recent vessel and incorporating the distribution of inter-arrival time between consecutive arriving ships, the ETA for each subsequent vessel can be inferred. Jung et al. (2018) develop a Bayesian inference and heuristics method to predict the destination port and ETA to the destination port of a given vessel. Onyshchenko and Koskina (2019) considers the different combinations of voyage charter-party (C/P) terms and their wordings, analyzing their impact on port stay time for the three most possible scenarios. The results obtained can be used for voyage planning and vessel's ETA prediction. Alessandrini, Mazzarella, and Vespe (2019) initially employ Dijkstra's algorithm (Dijkstra 1959) to conduct path searching for the remaining voyage.

Subsequently, Gaussian distribution is utilized to estimate the distribution of sailing speeds along the remaining voyage, thereby obtaining the vessel's ETA.

5.2. Machine learning models

Machine learning models have been demonstrated to be effective in various prediction tasks and are also the most widely used models in vessel's ETA prediction. These models demonstrate adeptness in integrating features from diverse data sources, and they also exploit known information more comprehensively than statistical models. Consequently, many researchers utilize machine learning models and have achieved promising model performance.

For basic machine learning models, linear regression (Kim, Kim, and Park 2017) and logistic regression (Pani et al. 2015) are deployed to predict vessel delay and ETA, where delay refers to the deviation of a vessel's actual arrival time from the average arrival time under normal sailing conditions. In addition, tree-based models (Chu, Yan, and Wang 2024; Lei et al. 2024; Pani et al. 2015; Valero et al. 2022; Yu et al. 2018) are also introduced to various scenarios to get short-term ETA prediction. Bodunov et al. (2018) achieve a 90% accuracy (measured in minutes) in ETA prediction by employing ensemble learning methods based on random forest (RF), gradient boosting decision trees (GBDT), extreme gradient boosting (XGBoost) trees, and extremely randomized trees (ERT). In vessel's ETA prediction, numerous data fields are categorical variables, and tree-based models are adept at handling such variables. For the ETA prediction of tankers, Xu et al. (2022) utilize trajectory clustering on AIS data to identify vessel historical voyage that matches closely to the current trajectory of concern. Subsequently, they incorporate weather data and port call information and utilize Support Vector Regression (SVR) models for ETA prediction in a more accurate manner. Salleh et al. (2017) develop an innovative fuzzy rule-based Bayesian network (FRBBN) to the arrival punctuality of a vessel and get reasonable prediction error.

Another advanced machine learning model is the multi-layer perceptron (MLP) or neural networks (NN). Jahn and Scheidweiler (2018) utilize NN based on AIS historical data and environmental data in 2016 and forecast for the next 24 h with an accuracy of Â±1 h. Mekkaoui, Benabbou, and Berrado (2022) use 180,000 rows of AIS data in the Mediterranean Sea for the period from 1 April to 28 April 2015 to predict vessel's ETA and prove that NN perform better than the other machine learning models in this task.

5.3. Deep learning models

The temporal characteristics and the substantial volume of vessel voyage data, coupled with other factors affecting vessel's ETA prediction, render such forecasting tasks ideally appropriate for learning through deep learning models. Nguyen, Le Van, and Ali (2018) discretize vessel trajectories into grids and employ a sequence-to-sequence model to predict vessel destinations and ETA. Through comparative analysis with alternative methods, this approach's efficacy was substantiated. El Mekkaoui, Benabbou, and Berrado (2020) integrate AIS data, LRIT data, and Terminal Operating System (TOS) data and utilize long short-term memory (LSTM) for vessel's ETA prediction. Comparative analysis against models including feed-forward neural networks (FFNNs), recurrent neural networks (RNN), LSTM, and gated recurrent units (GRU) reveal that LSTM performs the best. Noman et al. (2021) leverage historical data from both natural and artificial waterways to evaluate and compare the predictive capabilities of GBDT, MLP, and GRU in accurately forecasting ETA. Among these models, GRU exhibited the highest precision in their ETA prediction. Bourzak et al. (2023) choose vessel data from the Saint Lawrence River and compare the precision of vessel's ETA prediction across several models, including MLP, CNN, LSTM, bi-directional long short-term memory (BiLSTM), transformer, and a baseline method. The findings reveal that the BiLSTM model emerged as the best model in this scenario. El Mekkaoui, Benabbou, and Berrado (2023) tackle the ETA prediction challenge for bulk port vessels by incorporating diverse data sources and conducting a comparative analysis of four models: MLP, LSTM, 1D-CNN (Kiranyaz et al. 2019), and Wavenet (Oord et al. 2016). The findings highlight the superiority of sequence models over non-sequence ones while indicating a decline in performance for all models in short-term predictions. Abdi and Amrit (2024) develop a decision support system called vessel arrival time prediction (VATP), which utilizes AIS data, augmented information (Ain), and weather data. The results show that incorporating these additional data sources improves the accuracy of ETA prediction. Furthermore, the proposed VATP outperforms other models, including RF, ANN, support vector machine (SVM), CNN, FCL, LSTM, and BiLSTM.

5.4. Reinforcement learning models

In the domain of vessel's ETA prediction, reinforcement learning (RL) is a relatively rarely used model in existing literature. There is only one recent research paper using RL (K. Park, Sim, and Bae 2021). The authors propose a data-driven path finding method using AIS data, which can make RL agents achieve higher accuracy in trajectory prediction. Subsequently, they leverage Metropolis-Hastings algorithm (Chib and Greenberg 1995) to estimate the vessel sailing speed in the predicted trajectory and get the prediction of vessel's ETA.

Compared with machine learning and deep learning models, RL shares similarities in terms of input features and it relies more on dynamic information. Unlike traditional machine learning and deep learning models, which require retraining to incorporate new information, RL continuously adapts its strategies based on real-time vessel states and environmental conditions. With a large volume of training data, RL generally demonstrates better performance in vessel trajectory prediction, exhibiting comparatively lower variance.

To enable a more thorough comparison of the models and performances presented in the existing literature on vessel's ETA prediction, we have systematically organized the frameworks, vessel types, temporal and spatial scopes, models, and results of these studies in Table 4.

6. Future prospects

While existing research into vessel's ETA prediction has made notable strides, substantial opportunities for improvement persist. This section discusses three promising directions for future exploration and development in vessel's ETA prediction, namely enhanced information sharing, improved environmental condition forecasting, leveraging comprehensive features and integrating different frameworks, and integration with port operations management.

6.1. Enhanced information sharing

Enhanced information sharing among stakeholders in the maritime industry, including shipping companies, port authorities, vessel operators, cargo owners, and maritime service providers, is essential for improving the accuracy and reliability of vessel's ETA prediction. The future of maritime logistics relies on creating secure and decentralized platforms for real-time data sharing, including AIS data, vessel and port schedules, vessel sailing status and the reported ETA, and other relevant information. Blockchain technology presents a promising solution for ensuring data integrity and facilitating seamless information exchange between shipping companies, port authorities, and logistic providers. Future research should explore the development of the platforms that enable secure and transparent data sharing while protecting sensitive information. These platforms could use smart contracts to automate data transactions and ensure that all parties have access to accurate and up-to-date information. Improved data sharing can foster greater transparency and collaboration, allowing stakeholders to make more informed decisions.

Table 4. Summary of existing literature on vessel type, applicable range, model usage, and performance in ETA prediction problem.

Article	Vessel type	Temporal/ spatial scopes	Error/performance	Model/methods
Fancello et al. (2011)	Container ships	N.A.	5%-6% error rate	A dynamic learning predictive algorithm based on NN and an optimization algorithm
Du et al. (2013)[a]	Container ships	N.A.	N.A.	Statistical model
Pani et al. (2015)[a]	N.A.	N.A.	20% error rate	LR, classification tree, RF
Kim, Kim, and Park (2017)[a]	N.A.	N.A.	72% accuracy (detection of delay)	Self proposed method
Salleh et al. (2017)[a]	Container ships	N.A.	MAE from 1.008h (4.2%) to 1.584h (6.6%)	FRBBN
Jung et al. (2018)[a]	N.A.	N.A.	N.A.	Bayesian estimation
Jahn and Scheidweiler (2018)[a]	N.A.	About 24h	MAE (1h)	NN
Bodunov et al. (2018)[a]	N.A.	N.A.	90% accuracy	Tree-based model
Yu et al. (2018)[a]	Container ships	About 8h	69% accuracy	Back-propagation network, classification and regression tree, RF
Nguyen, Le Van, and Ali (2018)[a]	6 types, including cargo vessel, tug and oil tanker, etc.	N.A.	0.44 ppl (self-defined metric)	Sequence-to-Sequence models
Onyshchenko and Koskina (2019)[a]	Cargo ships	N.A.	N.A.	Statistical model
El Mekkaoui, Benabbou, and Berrado (2020)	N.A.	About 3000 km	MAE (0.23h)	LSTM
Veenstra and Harmelink (2021)[a]	N.A.	N.A.	N.A.	N.A.
Noman et al. (2021)[a]	Container ships	0–30 km	MAE (5.92min)	GBDT, MLP, GRU
Mekkaoui, Benabbou, and Berrado (2022)[a]	15 types of vessels	max to 4000 km	MAE (15h)	NN
Valero et al. (2022)	Container ships	N.A.	MAE (11.31min)	RF
Bourzak et al. (2023)[a]	Tugs, barges and merchant vessels	3000 km long river	MAE (0.229h), RMSE (0.408h)	MLP, CNN, LSTM, BiLSTM, Transformer
El Mekkaoui, Benabbou, and Berrado (2023)[a]	Bulk ships	About 2500 nmi	MAE (4h), MSE (70.15h)	MLP, LSTM, 1D-CNN, Wavenet
Chu, Yan, and Wang (2024)[a]	14 types in total	About 36h	MAE (15.5h),RMSE (11h)	RF
Kolley et al. (2023)[a]	General cargo vessels	About 5days (7200min)	MAE (100-120min, 4-8h time range)	Dynamic time buffers with ML(LR, kNN, DT, ANN)
Abdi and Amrit (2024)[a]	Container ships and tankers	350 km	RMSE (10h)	VATP
Lei et al. (2024)[a]	Multiple types	30 km	MAE (8.1min, downstream), MAE (15.4min, upstream)	Tree-based stacking model
Zhang et al. (2023)[a]	N.A.	1.14–1.30h	MAE (4.58min), RMSE (6.82min)	Temporal Convolutional Network (TCN) with residual mechanism
Guan, Cao, and Cheng (2024)[a]	N.A.	N.A.	MAE (30min)	Self-defined method
Alessandrini, Mazzarella, and Vespe (2019)[b]	N.A.	N.A.	Max error (1h)	Gaussian estimation
Kwun and Bae (2021)[b]	N.A.	0–800 km	MAE (0-600min)	A weight optimization A* algorithm

(*Continued*)

Table 4. (Continued).

Article	Vessel type	Temporal/ spatial scopes	Error/performance	Model/methods
K. Park, Sim, and Bae (2021)[b]	N.A.	< 600 km around port center	MAE < 5h	RL and bayesian estimation
Ogura, Inoue, and Uchihira (2021)[b]	N.A.	Japan-Taiwan & Japan-U.S.A.	MAE (4.6h)	Bayesian learning
Xu et al. (2022)[b]	Tankers	< 700 km around port center	Max error (2h)	SVR

[a]The study uses *Framework 1*: Non-trajectory-based prediction of vessel's ETA to port.
[b]The study uses *Framework 2*: Prediction of vessel's ETA to port by path finding.

6.2. Improved environmental condition forecasting

Environmental conditions, such as weather information and sea state, significantly impact the accuracy of vessel's ETA predictions. Enhanced environmental condition forecasting which will be integrated into ETA models can greatly improve prediction precision. Future research should aim to incorporate high-resolution meteorological and oceanographic data into machine learning models to enable more accurate adjustments to the predicted ETA based on real-time environmental changes. Advancements in remote sensing technology, such as satellite imagery and ocean buoys, provide an opportunity to collect detailed and timely environmental data. These data can be used to develop more robust predictive models that account for the complexities and uncertainties inherent in environmental conditions. For example, ensemble forecasting techniques, which combine multiple weather prediction models, can be used to provide more reliable estimates of weather impact on vessel navigation. Furthermore, developing adaptive learning systems that continuously update ETA prediction as new environmental data become available will be crucial. These systems should be capable of learning from historical patterns and real-time data to refine their predictions continuously. By improving the integration of environmental data into ETA models, the maritime industry can achieve more reliable and precise arrival time forecasts, leading to better voyage planning and reduced operational risks.

6.3. Leveraging comprehensive features and integrating different frameworks

To effectively address the uncertainties inherent in vessel's ETA prediction, future research should focus on the development and utilization of broader, more comprehensive features. Current prediction models generally rely on a limited set of features, which may not adequately capture the intricate and multifactorial pattern of maritime operations. By integrating a wider array of features, including dynamic route conditions, sophisticated meteorological information, detailed vessel operational behavior, and dynamic port conditions, current models can more accurately account for the diverse variables that influence a vessel's voyage. The inclusion of such extensive features has the potential to substantially reduce prediction errors by mitigating the impact of previously overlooked sources of uncertainty.

Existing research on vessel's ETA to port prediction typically employs either *framework 1* or *framework 2* as the foundational approach. However, in many real-world scenarios, the accuracy of ETA prediction can be further enhanced by dynamically selecting or integrating different frameworks based on the specific stage of the vessel's journey, which can be the departing from the origin, at high sea, or arriving at the destination. This adaptive strategy allows for the tailored application of either framework's strengths at different phases of the voyage, thereby optimizing the prediction process. By leveraging the distinct advantages of either framework at the appropriate stage, this method can potentially improve the accuracy and reliability of ETA prediction, offering a more nuanced and effective solution to the complexities of vessel's ETA prediction.

6.4. Integration with port operations management

The integration of vessel ETA prediction models with port operation management systems offers significant potential for maritime logistics. By incorporating accurate ETA predictions into port workflows, ports can optimize resource allocation, such as tugboat scheduling, berth assignments, and cargo handling, reducing vessel waiting times. This requires the development of sophisticated platforms that facilitate real-time communication and data exchange between vessels and port authorities. Future research should focus on building these integrated platforms, enabling dynamic adjustments in operational plans based on real-time predictive analytics. Leveraging internet of things technology and advanced data analytics could provide a holistic view of port operations, enhancing decision-making processes. For example, machine learning algorithms could predict congestion and recommend optimal docking schedules, minimizing delays and improving turnaround times. Within the Just-in-Time (JIT) framework, further exploration of precise ETA control could greatly benefit maritime supply chains. JIT's focus on reducing waste and ensuring timely delivery aligns with ETA-driven operations, enabling the synchronization of vessel arrivals with port activities. This integration would streamline resource use, reduce buffer times, and minimize excess inventory at ports, ensuring that vessels arrive 'just in time' and allowing for smoother transitions, lower costs, and increased throughput.

6.5. Usage of large language models

The application of Large Language Models (LLMs) in vessel's ETA prediction offers a potential solution to existing challenges, such as the varying quality and lack of standardization in data sources, as well as the prevalence of unstructured data. LLMs, with their advanced natural language processing capabilities, can parse and make sense of heterogeneous, unstructured data like weather forecasts, maritime news, and vessel logs, bridging gaps in data quality. By integrating LLMs into ETA prediction frameworks, the maritime industry can enhance the reliability of predictions, even when faced with inconsistent data sources, thereby improving resource allocation, such as tugboat scheduling, berth assignments, and cargo handling coordination.

However, these LLM-driven systems also present challenges related to computational power. While vessels can support onboard computing using engine-generated power to run local computational workloads, this approach comes at the cost of increased fuel consumption. Therefore, a hybrid strategy that optimally balances the use of local and cloud-based computation is crucial. Ships should leverage cloud computing when network conditions are available, minimizing the load on local resources to conserve fuel and reduce operational costs. Conversely, in regions with poor network connectivity, onboard systems should step in to maintain the functionality of predictive models. This dynamic allocation of computing resources ensures the continuous, efficient operation of LLMs, supporting real-time ETA predictions while mitigating environmental and fuel costs. Future research should focus on developing intelligent algorithms capable of dynamically switching between local and cloud computation, based on network availability and fuel consumption considerations, to further enhance the sustainability and efficiency of maritime logistics operations.

7. Discussion and conclusions

7.1. Difficulties in ETA prediction

Accurate prediction of ETA for vessels is a critical yet challenging task in maritime logistics. This subsection elucidates the primary factors that contribute to the complexity and inaccuracy of ETA predictions.

7.1.1. Data scarcity and quality issues

A fundamental impediment to precise ETA prediction is the shortage of high-quality, relevant data. Maritime operations generate vast amounts of data, yet much of it remains inaccessible or proprietary. Vessel tracking systems, such as AIS, provide real-time location data, but coverage can be inconsistent in remote areas where inland AIS receivers are unable to pick up the signal. Furthermore, the available data often suffers from quality issues. A significant portion of AIS data contains errors, including incorrect MMSI and inaccurate sensor data (Harati-Mokhtari et al. 2007; Mazzarella et al. 2013; Watson, Holm, and Lind 2015), which substantially impact ETA calculation accuracy. Additionally, as discussed in Section 3, a significant portion of the factors influencing the accuracy of a vessel's ETA prediction, such as human factors and external unexpected factors, are challenging to obtain and use in practice.

7.1.2. Multitude of uncertainty factors

Predicting vessel's ETA to port is inherently complex due to the multitude of uncertain variables involved. Weather conditions, particularly wind speed, wave height, and currents, influence vessel speed and, consequently, arrival time. However, meteorological forecasts carry their own uncertainties. Additionally, operational factors such as engine performance, fuel quality, and hull fouling can affect speed, yet these parameters are often not accurately quantified or communicated. Port-related uncertainties further compound the issue. Congestion levels, berth availability, and pilot scheduling can lead to substantial delays that are difficult to predict in advance. According to the survey conducted by Lu, Park, and Huo (2015) regarding leading container seaports worldwide, actual berthing time in many ports frequently deviates from scheduled time and significant inefficiencies exist in the production processes of the world's 20 leading container ports.

7.1.3. Insufficient data sharing

The maritime industry's fragmented nature exacerbates ETA prediction challenges. Key stakeholders—shipping companies, port authorities, terminal operators, and logistics providers—often operate in silos, resulting in inadequate data exchange. Shipping companies possess crucial voyage data, such as planned routes and vessel-specific performance metrics, but may be reluctant to share this information due to competitive concerns. Similarly, port authorities hold vital data on berthing schedules, tidal windows, and local navigational constraints. However, many ports do not provide real-time updates on these factors to shipping lines. This information asymmetry leads to disparities between a vessel's calculated ETA and the port's operational realities. Moreover, the lack of standardized data formats and communication protocols hinders effective data integration. Despite initiatives to standardize ETA data elements, industry-wide adoption remains slow. This fragmentation prevents the creation of comprehensive, real-time datasets necessary for accurate ETA prediction.

7.2. Limitations and future research

One of the key limitations of our review is the relatively small number of studies on vessel's ETA prediction, which restricts the ability to draw comprehensive conclusions or establish universally applicable practices in this area. However, it is important to note that the limited number of studies is due to the early stage of research in this field, rather than a result of restrictive criteria or selective inclusion. Another limitation is the insufficient description of the datasets used in many of the existing studies. The lack of detailed information on dataset characteristics, such as features, sources, and preprocessing methods, complicates comparisons of different research approaches. This issue is common in the existing literature rather than a limitation of our review. To enhance the comparability of future studies, it is crucial for researchers to provide more transparency in dataset reporting. Last, the classification of models and frameworks in this study is relatively broad and less specific, primarily due to the limited number of studies available. Future research could refine these classifications by distinguishing between specific types of models and methodologies which presenting more details of each single study covered, thereby providing a more nuanced understanding of their strengths and weaknesses.

7.3. Conclusions

This paper conducts a systematic review of the current literature on vessel's ETA to port prediction, including 29 papers published in academic journals and conference proceedings since 2011. First, the key factors influencing vessel's ETA prediction are identified and categorized into six major categories: vessel static information, dynamic information, route conditions, environmental conditions, human factors, and external unexpected factors. A detailed analysis of these factors underscores the inherent challenges in achieving accurate ETA predictions. Subsequently, we categorize existing research strategies into two primary frameworks, *framework 1*—non-trajectory-based prediction of a vessel's ETA to port; and *framework 2*-prediction of a vessel's ETA to port by path finding. Furthermore, the prediction models used in these studies are classified into four main categories: statistical models, machine learning models, deep learning models, and reinforcement learning models. This classification elucidates the diverse techniques utilized in the field and their respective contributions to advancing ETA prediction. Based on the above summary and review, we then explore potential future research directions, emphasizing the importance of data sharing, improved environmental condition prediction, incorporating more comprehensive features and dynamically integrating different frameworks to enhance prediction accuracy, and integration with port operation management. These prospective research avenues are crucial for addressing the existing challenges and refining the effectiveness of vessel's ETA prediction.

This paper is the first comprehensive review of the literature of vessel's ETA to port prediction. Accurate ETA prediction is the foundation of improving the efficiency of logistic system and port operation management. The insights presented in this review will be of significant interest to academic scholars, shipping industry professionals, and maritime policymakers. By enhancing the accuracy and reliability of vessel's ETA prediction, this work contributes to addressing a critical and pressing challenge within the maritime industry: optimizing operational efficiency and improving the reliability of maritime transportation.

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