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Scheduling, Berthing, and Cargo Handling Optimization Using Queuing Theory and Deep Learning

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Abstract: Maritime transportation is very important for global trade as it is responsible for 80% of movements of goods across the world. Considering the increase in freight movements, efficient system is needed for cargo handling and scheduling at ports. The existing "first-come-first-serve (FCFS)" approach is incapable to ensure operational efficiency under complex situations like parallel scheduling with various cargo setups. Data-driven strategies are much needed, given the rising demand. Robust berth scheduling is needed for conflict-free queuing of vessels in terminal, given the actual vessel arrival uncertainty, which may be caused due to sea current and cross wind.

Cargo handling is an important process in maritime logistics. Decisions like selecting proper equipment, type of ownership (outsourcing or in-house), and capacity to operation-based decisions like scheduling, resource allocation, and routing are important for efficiency of cargo handling systems. Different tools and approaches are used by industry experts to determine these handling systems to choose the best policies. This study explores previous works related to optimization and evaluation of cargo handling systems with queuing models. In addition, this study conducts comprehensive analysis through systematic literature review. It provides thorough understanding to industry practitioners and research scholars about queuing networks and deep learning methods used for berthing optimization.

Keywords – berthing, cargo handling, queuing models, deep learning, scheduling, maritime transportation

INTRODUCTION

Predicting unloading items is needed to reduce the cost of delay and schedule cargo operations smoothly (Gao et al, 2021; 2022). Accurate prediction of unloading items can form ideal conditions for smooth allocation of unloading resources for constantly arriving vessels. It can provide a buffer for succeeding operations of storage in the yard. There are thousands of ships in the steel and iron enterprise which transport millions of tons of materials to the terminal every year. These vessels should be unloaded properly to reduce delay expenses and meet needs for production. When ships fail in timely unloading because of different reasons, companies bear huge demurrage costs that could be hundreds of millions every year.

Unloading time of vessels can be influenced by two major factors – schedule for unloading ship setup at the terminal of raw materials and storage operation schedule for raw materials adopted in stockyard. Figure 1 illustrates the ship-unloading of a steel plant. This system typically includes various berths, few ship unloaders, and a conveyor system for transmission. The berths are assigned for docking of ships with raw materials, while unloaders unload the raw materials. These unloaders can go along a specific track. Smaller vessels usually under 50000 tons are enough for meeting unloading needs (Gao et al, 2024).

For larger vessels above 150,000 tons, it is worth allocating 2-3 unloaders to enhance the operations. The conveyor is installed around the whole port area, production areas, and stockyard for bi-directional transfer of products and raw materials among such areas (Gao et al, 2024). When a ship arrives at the terminal of raw materials, multiple ship unloaders and berth are assigned for unloading. At the same time, there is a need to designate storage space for unloaded materials in the yard. Accuracy in predicting the unloading time can generate space for buffer for constant schedules of dock-unloading and allocation of storage space. These improvements help in reducing the cost of delays, execution of operations, and improves efficiency, making it ideal for port operations.

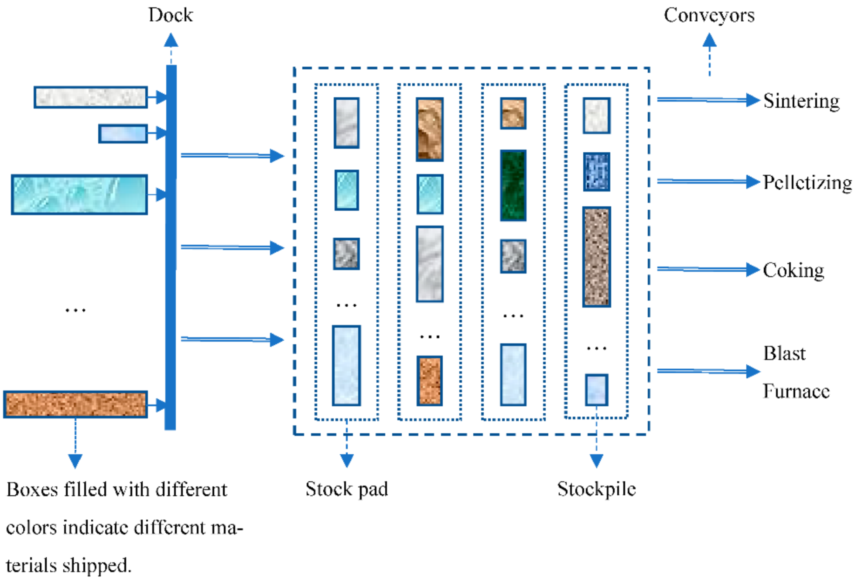

Figure 1:A flowchart of vessel unloading in a manufacturing unit

Source – Gao et al (2024)

Maritime transportation is the most important contributor for globalization and economic growth of the nation, covering global trade with huge cargo volumes (Elmi et al, 2022). Seaborne trade has been an important mode for global transportation over the years, as per the statistics for global commercial exchange. Maritime transport manages over 80% of global trade and this share is even higher for majority of developing countries. There has been a rise in seaborne trade by 3% in a year over the past four decades, as reported by UNCTAD (2022).

In supply chains, the “marine container terminals (MCTs) play a vital role in receiving or delivering containers to and from ships across various operators and linear shipping companies. The rise volume of maritime transport has a lot of challenges for operators like allocation of mega ships, congestion at ports, and efficiency of ship service (Kumawat and Roy, 2021). To deal with steady and rapid growth of maritime market, operators need to address operational issues with right analytical approaches for aligning with market situations (Moon, 2000).

In order to improve port productivity and retain customer satisfaction, operators should make the most of their berthing and handling resources (Carlo et al, 2015).

In order to improve port efficiency and customer satisfaction, cargo operators should make the most of their berthing and handling resources (Carlo et al, 2015). Adopting the right berth scheme usually improve productivity and competitiveness over other marine terminals. Optimizing berth schedule has a robust association with planning temporal and spatial resources. When it comes to arrive at marine terminal, ships usually wait for scheduled position that would be ideal for terminal operation and available (Cordeau et al, 2005). Berth scheduling and allocation can be a challenge which should be addressed by operators as they may affect deployment of port equipment and allocation of storage spaces (Xu et al, 2012).

A group of vessels arriving are supposed to be served in the certain horizon for planning in “berth allocation and scheduling problem (BASP)” and configuration of berth is specified. The assigned position of berthing refers to the range of operation of quay cranes which are allocated and same berthing space and equipment are not usually assigned to multiple ships. The direct goal of BASP is providing a schedule for each vessel arriving with optimal timing and berthing position, while avoiding issues (Bierwirth & Meisel, 2010, 2015).

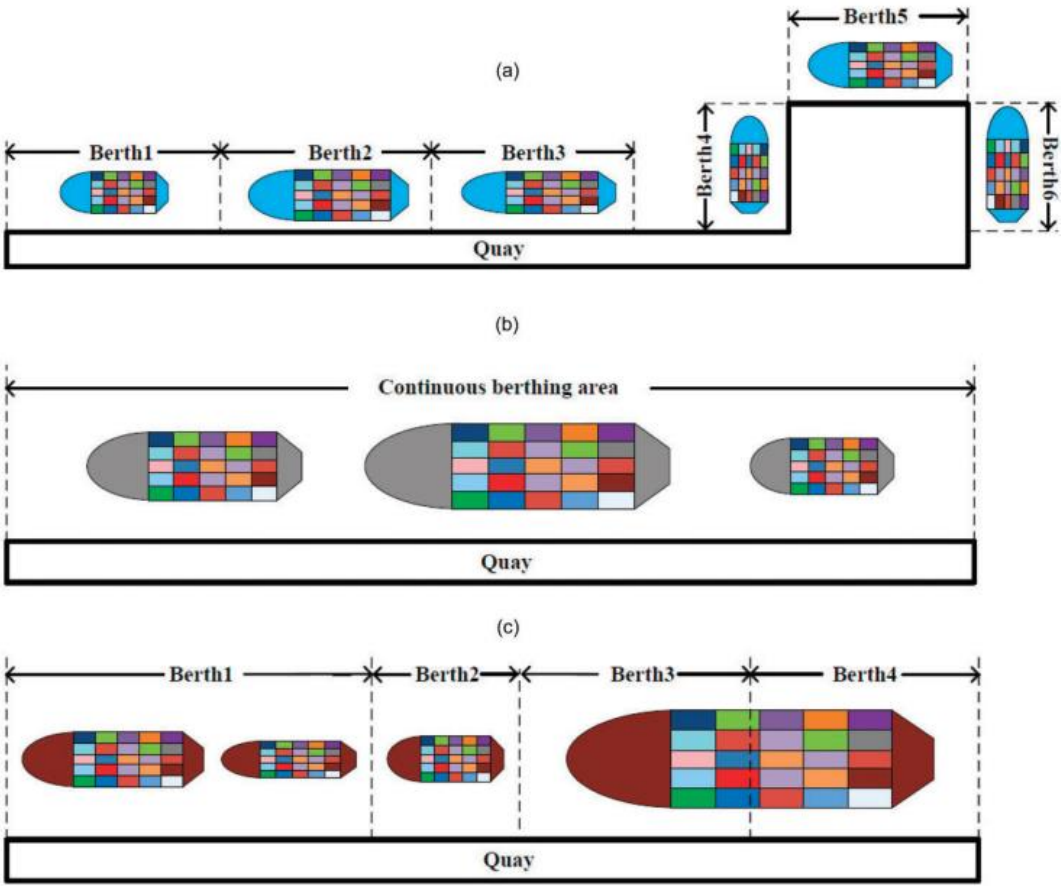

Figure 2: Types of Berthing layouts – (a) Discrete (b) Continuous and (c) Hybrid

Source – Li et al (2023)

LITERATURE REVIEW

Several studies have been conducted to predict loading and unloading time which can be based on scheduling, storage operations in stockyard, and using deep learning and deep neural networks to predict unloading time.

Scheduling

Dhingra et al (2017) have proposed a 2-level "stochastic model" to determine the handling time of container ship. A constant-time Markov chain is employed by the higher-level model to determine the unloading and loading time, while lower-level model used a "closed queuing network" for transition matrix as input. Bish (2003) addressed the scheduling problem of loading and unloading of container with a set of ships, given the storage location of each vessel, scheduling of cranes for unloading and loading, and assigning vehicles to containers. The goal was to reduce the maximum time needed for serving several ships. This problem was solved by a heuristic approach and its effectiveness was analyzed well.

Al-Dhaheri et al (2016) proposed a “stochastic mixed-integer programming model” to reduce handling time of container ship. A genetic model constructed the crane schedule while following the operational rules to manage the use of cranes. Sun et al (2019) investigated the problem of “quay crane scheduling” to reduce the time to complete “loading and unloading” operations for ships. They proposed a “Benders decomposition method” and “mathematical programming model” to solve the issue. Sammarra et al (2007) proposed a “tabu-search heuristic” model for scheduling quay crane, based on reducing the time to complete loading and unloading for containers.

They considered certain operational limitations for quay cranes, disintegrating the challenge into a scheduling and routing problem, which could be addressed with “local search and tabu search heuristic technique”. Tang et al (2014) proposed a joint scheduling method for trucks and quay cranes for servicing the containers. They introduced a “particle swarm optimization (PSO)” approach to deal with scheduling problem. Kao et al (1990) proposed a “knowledge-based approach” for scheduling container to mitigate demurrage costs. Their knowledge base can handle the transfer of ships and sequencing of waiting ships among two docks.

Kao et al (1992) proposed a heuristic method for scheduling discharge of ships. Their approach assigned ship unloaders, stackers, conveyer belts, and sequencing of holds. Kao and Lee (1996) proposed an integrated system for coordinating ship discharging and dock assignment with an integrated ship unloading system to improve the efficiency of unloading. Kim and Moon (2003) introduced a “mixed-integer programming (MIP)” model for addressing the problem of berth-planning. Each ship can stay for a specific duration in their approach, despite of berthing locations. The problem can be solved with a simulated annealing model. A ship-unloading issue is investigated by Kim et al (2011) for a large steel plant to reduce the overall flow time of all ships at the port. This challenge was addressed with a heuristic model. Gao et al (2021) evaluated the scheduling of unloading of ship in a big steel plant. They proposed a “column-generation model” and proposed a mathematical model to solve the problem. In addition, a “differential evolution model” is proposed by Gao et al (2022) for scheduling ship-unloading with special emphasis on assigning belt conveyors.

Storage Operations

A “mixed-integer programming (MIP)” model is proposed by Lee et al (2009) for allocating storage and scheduling yard trucks. They are aimed to reduce the “weighted total cost”, which consists of penalties for overall delays and costs related to total time for traveling. For the MIP model, a “constructive heuristic” model was developed and made a 10.27% solution gap in comparison to CPLEX. For the heuristic, solution time was at another level, while 30 to 40 hours are needed by CPLEX to find solution.

Tang et al (2022) investigated the problem of allocating stockyard space at a large terminal of iron ore. They designed a “mixed-integer linear programming model” in order to reduce the total distance of travelling for all iron ores incoming. The major limitations are operations of “stacker-reclaimers” and managing “space allocation”. The “genetic model-based heuristic” was used to solve the model. Heuristic can get ideal solutions for smaller problems in seconds. CPLEX cannot find ideal solution in 2 hours for larger problems, while heuristic can deliver almost optimal solutions within seconds.

Li and Tang (2005) addressed the problem of allocating storage space in an iron and steel stockyard by introducing a “non-linear programming model.” The goal was to reduce the penalty and transportation costs, with limitations related to length, height and width and differences in types of materials for spatial allocation. This issue was resolved with enhanced tabu search model. A problem of allocating storage for raw materials was examined by Kim et al (2009) for large steelworks plant. They proposed a mixed-integer model for linear programming, solved with CPLEX 9.02. The constraints of the model maintained a safe distance among two stockpiles to ensure the balance of materials.

Deep Learning for Optimization Problems

Vinyals et al (2015) proposed a special kind of Deep Neural Network (DNN) called pointer network and trained the same to output for “traveling salesman problem” with supervised learning. This pointer network was trained by Bello et al (2016) for “traveling salesman with reinforcement learning”. A similar approach was proposed by Kool and Welling (2018) which can also solve other routing issues like “vehicle routing problem.” A “graph embedding network” is trained by Khalil et al (2017) with reinforcement learning to provide solutions for graph problems like maximum cut problem and least vertex cover.

All methods have focused on architecture and training of DNNs rather than how to adopt DNNs in a smart search protocol. Despite having promising results, the methods cannot compete with state-of-the-art methods on wider instances. DNNs have recently been used in terms of “constraint satisfaction problems (CSPs)”. Xu et al (2018) have used a convolutional DNN successfully for the prediction of satisfiability of “random Boolean binary CSPs”. Galassi et al (2018) investigated learning of DNN to build a CSP solution by training the same to make individual variable assignment with supervised learning.

Several variants of neural networks have been deployed to perform classification and prediction. A probabilistic neural network has been proposed by Zhang and Shin (2022) to monitor the processes of manufacturing. The distributed parameters of Gaussian mixture has been featured in this network to improve computational efficiency. A “long short-term memory (LSTM)” neural network has been developed by Li et al (2022) for “time-series prediction” using “partial least squares (PLS)” to ease the network architecture. Strong generalization potential is balanced with compact structure smoothly with LSTM framework. A “Backpropagation Neural Network (BP)” is employed by Xiao et al (2009) which is combined with “rough set theory” for forecasting power load with rough sets to reduce dimensionality. This method has improved prediction outcome.

Adelia and Panakkat (2009) proposed a “probabilistic neural network” to forecast the magnitudes of earthquake. Kosanoglu (2022) introduced “ensemble model” integrating deep learning models and “time-series clustering” approaches for forecasting wind speed. A “Dirichlet mixture model” and “dynamic time warming” techniques were used to cluster factors from “time-series data”. It is observed that “feature-clustering approach” is a promising model for prediction. A “Machine Learning” model is developed by Hussein et al (2019) to combine “random vector functional link (RVFL)” network with “moth search” model for predicting missing values of “total algal counts” while monitoring water quality. The input features were optimized by the moth search model for RVFL network, resulting in algal values predicted which has matched true observations closely.

Four ML models were proposed by El-Said et al (2021) – “support vector machine, RVFL, K-nearest neighbors, and social media optimization” to determine the effect of transverse baffles and air injection on “thermohydraulic” effect of tube and shell heat exchangers. It is found that non-linear relations were identified effectively between process responses and operating conditions by the RVFL model. An SCN model is introduced by Wang and Wang (2020) to predict the concentrations of components in "sodium aluminate liquor". This mechanistic model clarifies the relation between temperature, conductivity, and concentrations of components in "Bayer alumina production" with indication of high prediction accuracy. An enhanced SCN model is proposed by Li et al (2023) to predict "ammonia nitrogen concentrations" in tracking water quality. They brought a new inequality in the process of network concentration and introduced the approach of node-selection.

Research Gap

When it comes to queuing models, current studies are based mainly on static queues without considering challenges of real cargo operators like different types of cargo, availability of cranes, and dynamic arrival of vessels. Deep learning is also evolving in maritime studies. But there is still a huge research gap in its use in prediction of arrivals and real-time scheduling. Existing studies are based on image-based inspection and tracking containers. Cargo management and berthing are usually optimized individually. There is also a lack of frameworks integrating queuing theory and deep learning for developing a real-time berth scheduling system.

Research Objectives

- To discuss queuing network models used for cargo handling operations
- To explore deep learning-based methods for cargo scheduling and handling arrival uncertainty
- To propose a robust berth scheduling framework to optimize material handling across ports

RESEARCH METHODOLOGY

This study is based on a thorough process of literature review for a comprehensive analysis of literature. This study is based on content analysis approach for a comprehensive literature search on scheduling and berth allocation.

For a literature search, this study is based on search through search databases like IEEE Explore, Springer Link, Web of Science, Scopus, and Google Scholar. A lot of keyword combinations were adopted for the search process, including berth scheduling, allocation, hybrid berth allocation, deep learning, queuing theory, etc.

After conducting initial search, this study has discovered hundreds of relevant studies. It is primarily based on articles writing in English and published in peer-reviewed journals, doctoral theses, and conference papers. Studies written in other languages were not considered. In addition, studies dealing with other operations were not considered.

DATA ANALYSIS

Queuing Network Models for Cargo Handling Operations

For smooth flow of materials to target destinations, cargo handling is critical for logistics operations. These activities are responsible for 15 to 70 percent of total costs of manufacturing as per the product type (Soufi et al, 2021). In the same way, 55% of operational costs in warehouse include activities related to cargo handling (Tompkins et al, 2010). In the warehouse storage, 10.8 million people were employed in the European Union (EU) for EUR 556 million (Eurostat, 2018). Cargo handling systems are critical for moving raw materials, finished goods, and work-in-progress from one destination to another.

These points consist of warehouses, production floors, shipping, and storage areas. In general, the process of manufacturing consists of assembly operations and fabrication activities changing the shape, make-up, and form of material. It is possible to use cargo handling systems for place and time utility" with storage, control, and handling of materials (Furmans, 2009). The most important decisions related to cargo handling swivel around "material handling equipment (MHE)". Selecting the right equipment and integrating the same with logistics operations of organizations are important for achieving low costs of handling materials (Stephens, 2020). Kay (2012) proposed ten principles combined by Material Handling Institute (MHI)" when it comes to design cargo handling systems.

There is a need to consider standardization, planning, ergonomic, work, space utilization, unit load, lifecycle and environmental principles, and automation when designing cargo handling process. All these are bound by operation and selection of equipment for cargo handling. Such equipment can be classified into sub-categories on the basis of its technology, operation, and application. Some of those categories are hoists, manual systems, pipe systems, industrial trucks, automated guided vehicles (AGVs), robotic systems, bulk load conveyors, and unit load conveyors (Bouh and Riopel, 2016). MHE is classified into cranes and hoists, conveyors, and transporters (Smith, 2013). The materials are transported by conveyors into fixed path. Hoists and cranes can transfer material over specific data. Transporters can carry material over larger region. Figure 3 illustrates a tree structure of material handling equipment (MHE).

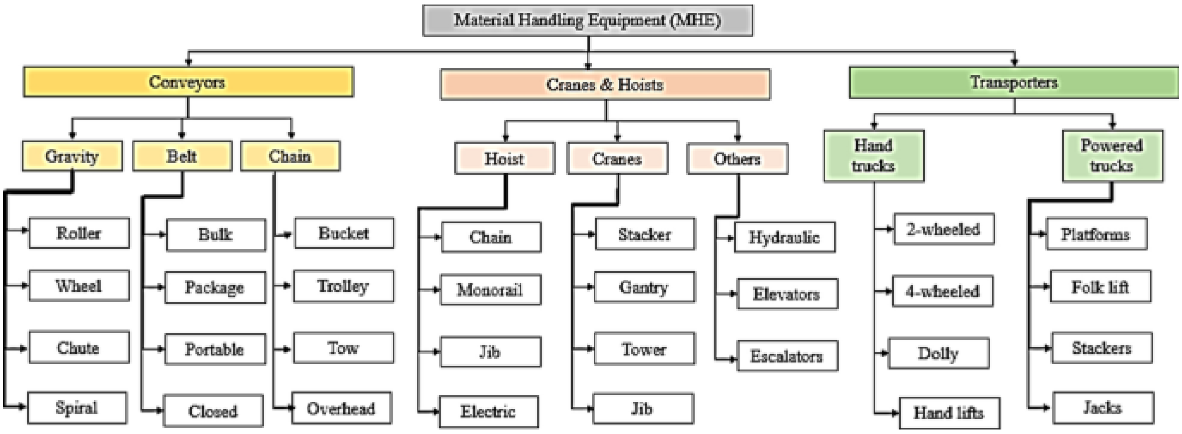

Figure 3: A tree structure of MHE

Source – Smith (2013)

When it comes to set up cargo handling, major design decisions can be classified into features related to design and operations. Figure 4 lists both design and operation features of MHS (Raman et al, 2009). Other factors relying on specific needs of industry must be considered when it comes to choose the right equipment. For example, there are certain issues in “semiconductor wafer fabrication system (SWFS)” like flexible routes, WIP, and longer time for production cycle (Chen et al, 2017a, 2017b). Higher responsiveness is much needed to deal with unpredictable arrivals. After selecting the right equipment, there is a need to probe the overall efficiency of cargo handling to determine productivity of the system. It is critical for industry practitioners to assess performance of cargo handling systems (Sahu et al, 2017). Characteristic factors of variability like congestions, irregular arrivals, human involvement, changes in demand and supply, product blending, resource breakdowns, and capabilities of machines may make it complicated to optimize and assess the performance of cargo handling (Lee et al, 2021).

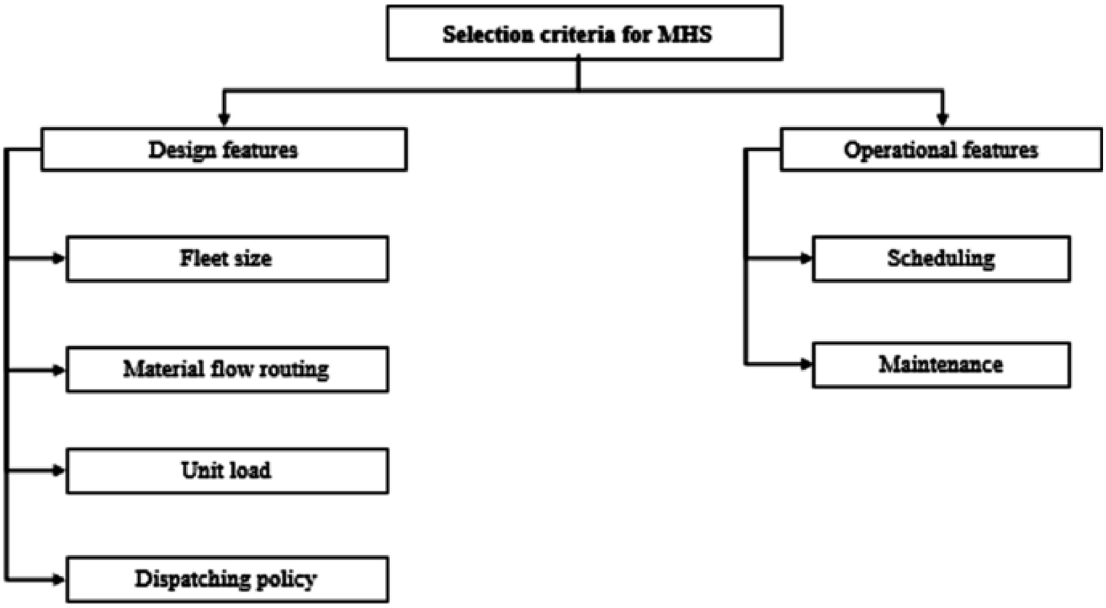

Figure 4: Operation and Design Features of MHS

Source – Raman et al (2009)

Initially, queuing network models are utilized to measure communication and computer systems performance like server usage, mean response times, and queue lengths. These frameworks have been used widely in several fields like transportation, production, service, and retail sectors. Queuing models are often known to be versatile, cost-effective, and strong tools to analyze complex systems with short computation and development time (Balsamo et al, 2003). Queuing models are more realistic with blocking phenomena to inculcate limited queues of capacity for real applications in different areas. In the same way, queuing models can be used for modeling MHS in several nodes of supply chain like distribution centers, warehouses, terminals, and intermediate storage. As these models are usually stubborn mathematically, a lot of studies have focused on approximations and heuristics to assess the performance measures (Smith and Kerbache 2012).

Queuing network consists of a range of queues and these networks can be classified on the basis of several factors. A lot of networks can be observed in the study. For instance, there are three types of queuing networks – closed, mixed, and open, as per the circulation of population in the network. In the same way, it is possible to find several types of networks on the basis of characteristics of network like customer classes, distribution of probability, number of servers, server capacity, queuing capacity, and blocking system. Figure 5 illustrates queuing networks classified as per the above features over the generality index and complexity of network. However, it is possible to find different kinds of queuing networks in studies as per various characteristics.

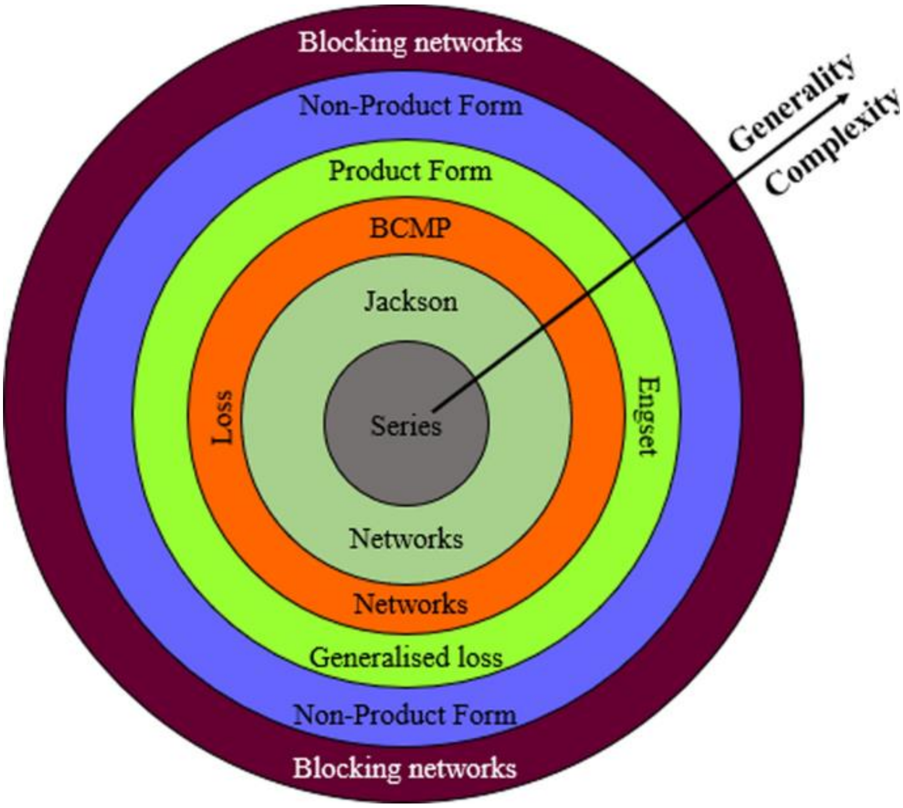

Figure 5: Series of Queuing Networks

Source – Smith (2018)

As per their complex mathematics, it is possible to solve queuing network models with actual analytical product from simulation, approximate models, and methods. In general, it is possible to solve smaller models for queuing network. Usually, approximation approaches are used for more complex networks of queuing. Figure 4 and Figure 5 list the approximation and exact methods for solving different queuing models.

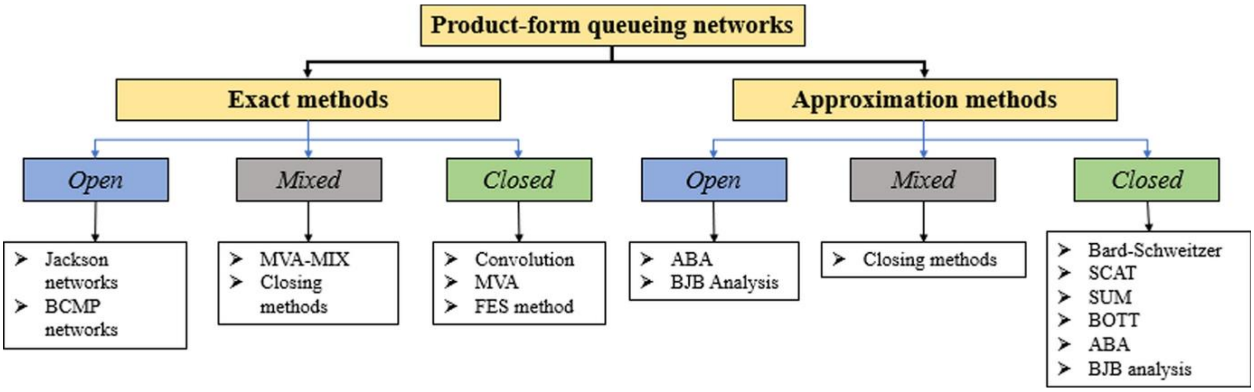

Figure 4: Solution models for queuing networks in product-form

Source – Bolch et al (2006)

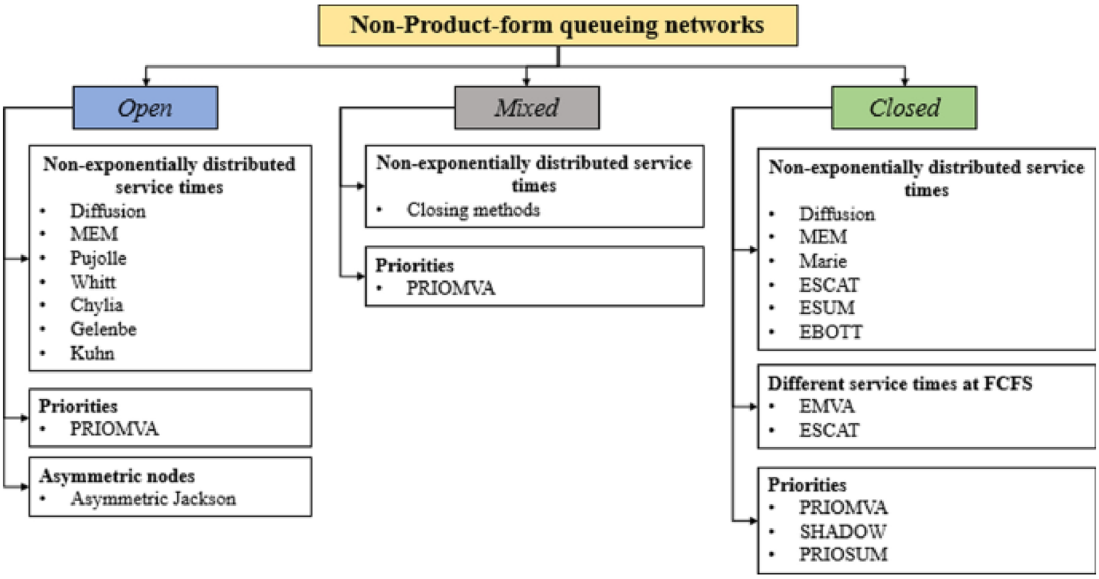

Figure 5: Solution models for queuing networks (non-product form)

Source - Bolch et al (2006)

In the queuing network, performance measures include queue waiting time, length, response time, throughput, server usage, and cycling type measurements. They provide important insights to the process of decision-making in a specific network. For instance, queuing throughput can model a container terminal to provide insights to operational productivity of the terminal. In the same way, using network node gives an idea of idleness or congestion of the resource. There are three parts of derivation of optimization problem. There is a need to determine the ideal value of variables, while fulfilling the given limitations by achieving a planned objective.

Associated with queuing models of cargo handling, optimization problems can be derived in the same way. Figure 6 illustrates the relation between them. For example, an optimization problem can be considered to determine the right arrival rate of trucks to achieve optimum throughput in the warehouse. Subsequently, the ideal arrival rate will bring change in all measures of network performance. In addition, optimization problems are based on multi-objective or single-objective problems. Those approaches are ranging from actual solution models to heuristic on the basis of magnitude and complexity of issue. In order to estimate performance of network, approximate approaches provide the right deviations from actual solutions.

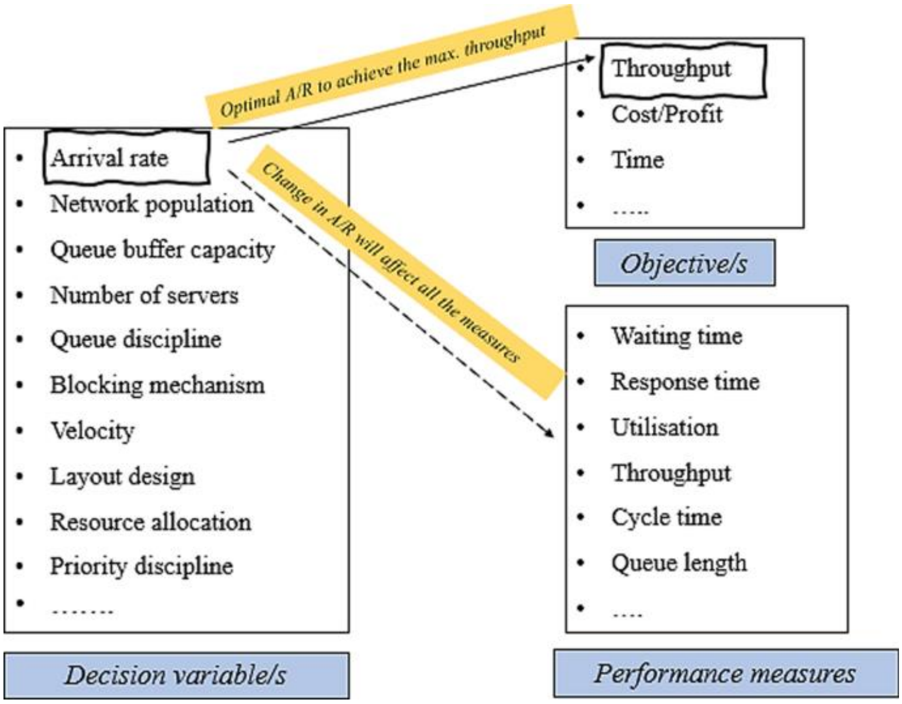

Figure 6: Interaction between parameters and variables in optimization problem of queuing models

Source – Amjath et al (2024)

Deep Learning Methods for Cargo Scheduling and Handling Arrival Uncertainty

Marine transport is a very important mode for global and domestic trade because of eco-friendly nature and large capacity. International economic expansion has improved the need for larger vessels for marine transport these days. In addition, shipping has been vital to transport goods for longer distances. More than 90% of global trade is being shipped by ships (Lechtenberg et al., 2019). In this case, several vessels are loaded and unloaded in a port every day. Some of the major issues for maritime transportation are terminal operations which include (1) berth allocation and scheduling in harbors; (2) Human resources (working shifts for incoming vessels); (3) yard planning; and (4) allocation of equipment or spatial and mechanical resources (Ambrosino & Tanfani, 2012; Di Francesco et al., 2015; Ku et al, 2012).

In supply chains in ports, a major issue takes place from the uncertainty related to arrival times of vessels, leading to disrupted port planning (Gómez et al., 2016). In addition, costs related to supply chain result in overall expenses related to transportation (Zuidwijk and Veenstra, 2015). Hence, improving the accuracy of prediction of arrival times reduce the cost of supply chains. Additionally, it is possible to improve the competitiveness of supply chain in the terminal as terminal efficiency can be improved while reducing the operation cost.

Whole logistics process can be conducted smoothly if it is possible to predict the arrival time of the ship accurately as resources can be assigned efficiently. With accurate arrival of ship, resource allocation and decision-making of investment can be improved as well (Mensah and Anim, 2016). It has been observed to provide a lot of benefits to a port when it comes to plan terminal operations smoothly, improve efficiency, and cost savings (Meijer, 2017). It is also worth making decisions in scheduling and activities in different areas like docks, ships, and yards while meeting various needs.

The “Automated Identification System (AIS)” is a safety mechanism of maritime traffic and navigation enforced by the IMO. With gross tonnage above 300 MT, all vessels can have AIS system. Data from the AIS system can be useful for different applications like security, maritime surveillance, vessel monitoring, rescue, security, collision prevention, and traffic control (Sampath & Parry, 2013). Figure 7 illustrates factors affecting the vessel’s arrival time and shows different subfigures (like weather data, sea data, AIS data, and ship details) giving an insight to these interlinked elements and their effect on arrival of ship. Details on sea currents are helpful to understand the challenges faced by ships in their voyage.

The weather details include wind speed and other meteorological data to assess the effect of weather on arrival time and performance of the vessel. The ship info includes size, time, and other vessel information. Finally, AIS dataset includes real-time data of ships like speed, position, etc. for assessing possible delays and efficiency in navigation. Figure 7 illustrates several factors responsible for arrival time of the ship, decision-making, and analysis for optimal management and planning.

Figure 7: Factors affecting ship's arrival time

Source – Sampath (2012)

Each vessel emits plenty of signals regularly during the journey, which are then accepted by ground stations, other ships, and satellites (Figure 8). The AIS dataset provides several dynamic details like course, speed, position, etc. and static details like MMSI, ship type, and ship name. Table 1 illustrates the fields included in AIS dataset along with their description.

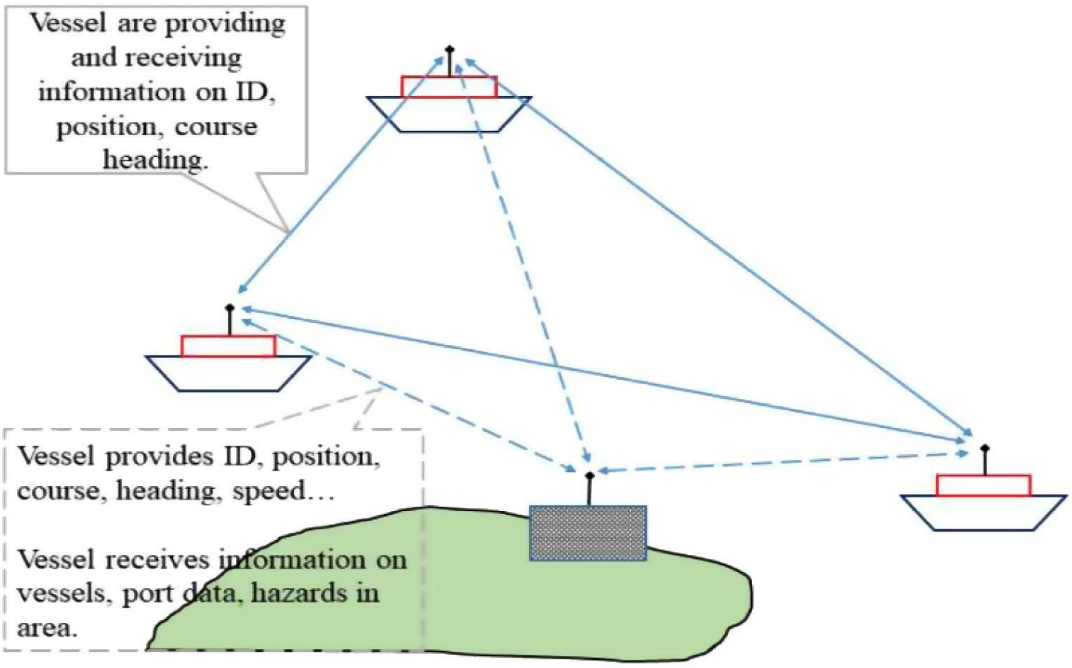

Figure 7: An overview of AIS system

Source - Lee et al (2019)

Table 1: Fields of AIS Dataset

Fields	**Explanation**
Ship name	Ship’s name
Destination	Port where ship needs to reach
Heading	Vessel’s heading in degrees
MMSI	It refers to “Maritime Mobile Service Identity” – a 9-digit unique ID number of the vessel
Longitude	Longitudinal position of the vessel
Latitude	Latitudinal position of the vessel
IMO number	It is a unique identifier “International Maritime Organization” number of a ship
Draught	It is a vertical distance among the waterline and keel of the ship
ETA	“Estimated Time of Arrival” of the ship
COG	Course Over Ground is the vessel’s direction in decimals
SOG	Speed Over the Ground – it determines vessel’s speed corresponding to the earth surface
Timestamp	It is the time when report was generated by “electronic position system (EPFS)”
Ship type	It refers to the ship type like Cargo, Tanker, Military ops, Passenger, Fishing, etc.
Zone	It refers to the zone where ship is based on
Navigation status	It suggests ship’s status like “not under command, at anchor, aground, moored, underway sailing, etc.”

Source - Abdi and Amrit (2024)

Abdi and Amrit (2024) derived “vessel information” from Marine Traffic using MMSI and IMO, which is complementary to AIS dataset (Figure 8).

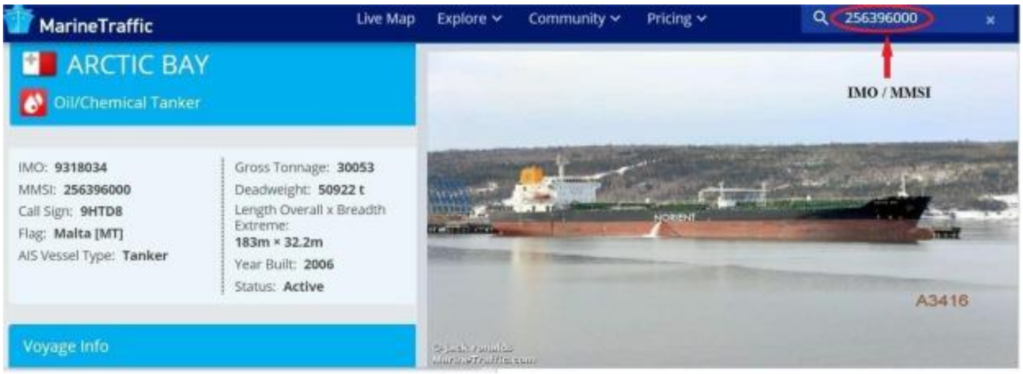

Figure 8: Vessel Information with AIS dataset

Source – Abdi and Amrit (2024)

Weather and sea information can be used to improve the forecasting performance of vessel arrival time. An AIS data provides weather information for maritime transportation, instead of marine weather information. Abdi and Amrit (2024) presented a “Deep Learning Based Method” for forecasting arrival time of the vessel by majorly using “Design Science” approach for “Vessel Arrival Time Prediction (VATP).” This approach is based on generating practical solutions, like creating viable artefact to evaluate its effectiveness (Hevner et al, 2004). Some of the key principles are clear contributions to practice and design theory, rigorous approaches, and relevance of the problem (Hevner et al, 2004). The phases of data analytics are linked to provide more accurate forecasting. These are CNN, LSTM, data pre-processing, LSTM, Dropout, attention mechanism, etc.

Berth Scheduling Framework to Optimize Material Handling Across Ports

There is a huge range of studies conducted on “Berth Allocation Problem (BAP)” and its variants. Carlo et al (2015) and Bierwirth and Meisel (2015) have conducted research on classification scheme related to BAP. Kolley et al (2023) conducted a study on the constant quay and fixed handling times on the dynamic berth scheduling framework with specific arrival times of vessels. They focused on berth allocation under uncertainty on proactive methods along with using time buffers. Liu et al (2020) provided a structured insight to relevant studies on berth scheduling under uncertainty.

Scenario-based approach is widely recommended to handle uncertainty in berth scheduling procedure. Along with scenario-based and proactive first-stage, Liu et al (2020) also considered recovery operations and potential disruptions on the reactive stage of second model. To be specific, they posited that possibilities needed are unknown in scenario-based method which are hard to derive. Hence, robust approach is ideal when it comes to manage uncertainty.

Time buffers are needed to develop such a strong approach and reduce uncertainty. Xu et al (2012) considered uncertain times of arrival and handling and suggested to mitigate uncertainty for robust berth scheduling. In contrast, space buffers are used instead of time buffers by Wu and Miao (2020) as they add some slack to the berths rather than focusing on fixed position for each ship and they aimed to improve flexibility while aiming for robustness. While they can suggest that expected waiting time can be reduced and costs, efficiency may also be affected when too much capacity and space is reserved for each ship.

Wang and Guo (2018) have studied the “Berth Allocation and Quay Crane Assignment Problem (BQCAP)” with unexpected times of arrival. They considered unexpected times and aimed for better quay cranes and berth scheduling. They considered uncertain times of arrival and aimed to make robust schedule for quay cranes and berths. Similarly, uncertain times for handling is considered by Rodriguez-Molins et al (2014) along with using variable time buffers for BQCAP. A proactive approach is adopted as per the scenario for this problem by Li et al (2019). Zhang et al (2014) have studied both handling and arrival times in the BQCAP, who assigned time buffers proactively with vessels. It is observed that proactive methods are needed for uncertainties in dynamic berth scheduling and buffers can be used to improve the robustness of scheduling proactively. These features can be used in this method to allocate individual buffers to various vessels, as per the level of uncertainty in arrival time.

When it comes to derive forecasts of arrival times of vessels, the overall process is illustrated in Figure 9. The steps of pre-processing, selecting, and data cleansing are important before extracting the data (Heilig et al, 2020). Only recent entries should be considered from the past AIS data for data selection as overall characteristics of the fleet may change over time because of bigger proportions of vessels and transport potential. Hence, AIS data are used from 2018 in this study. Data focusing on ending of the trip at the given port is relevant.

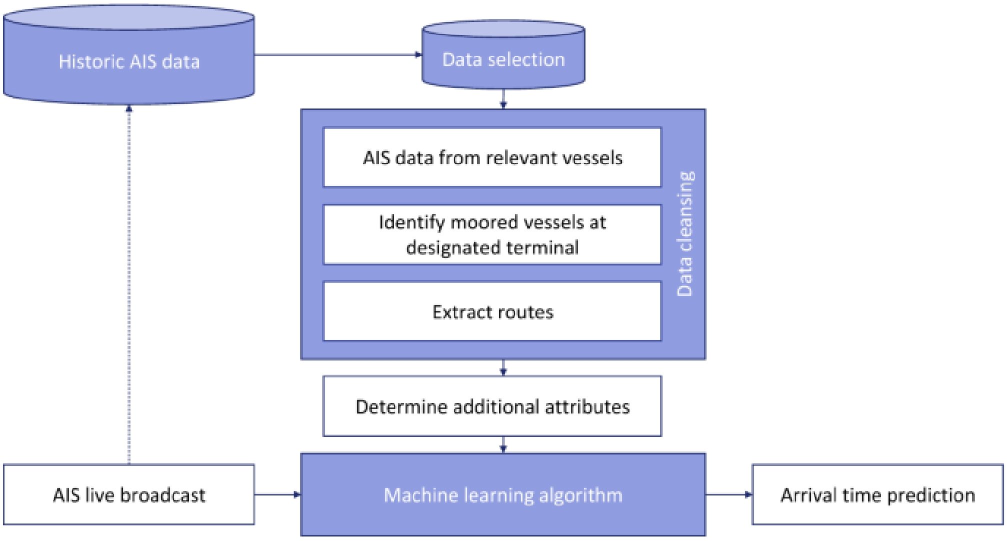

Figure 9: Steps involved in data pre-processing for arrival time prediction

Source – Kolley et al (2021)

Given the actual arrival times of all vessels from the previous data, the actual travel time remaining can be estimated for each AIS message from the approaching vessels to the port. The AIS signal from the vessel are sent to the reverse order and changed into the status attribute. In the trajectory, the AIS messages can be followed back until data is disrupted for two or more hours.

As those disruptions show the entry of ships on the area covered by AIS stations on the shore, a longer period of AIS messages missed or time spent be vessels at anchorage or spent in other ports, trajectory is ended. For the prediction of arrival time, the AIS message, which is previous or earliest, marks the beginning of approaching terminal. Rest of the AIS messages irrelevant to the approach of vessel are removed. Along with the rest of Euclidian distance, the draft between heading and COG is collected from the AIS messages (Kolley et al, 2021).

The relevant AIS messages are illustrated for the Miami Port are plotted on a map from 2018 to 2020 (Figure 10). Vessels are definitely approaching Miami from several origins. Vessels operate in a wide area in the south and east of Florida and can overtake one another. Hence, each ship can operate at their respective speed without considering congestions. As per the trajectories, most of the approaches are from north to east, while west trajectories are light and narrow in color because of lower density and less approaches of AIS messages. More complex models might use those properties on the basis of coordinates of vessels.

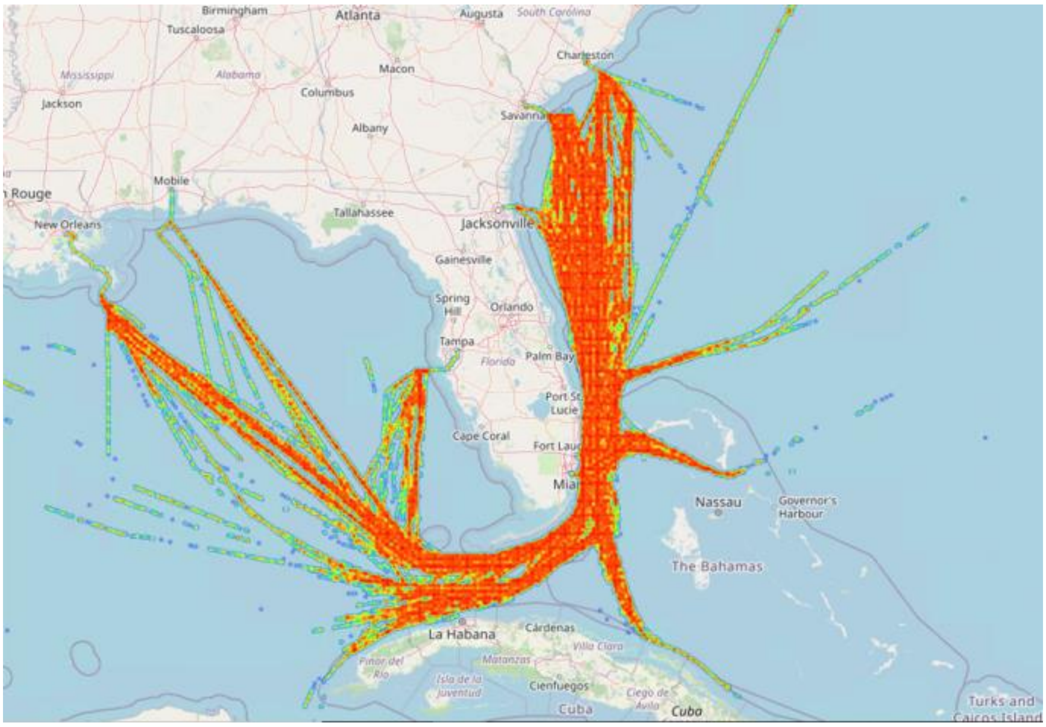

Figure 10: Heatmap of vessels approaching Miami port

Source – Kolley et al (2021)

In addition, approaches are visible at the terminals of other ports but couldn't be identified and not removed in the process of data cleansing. It is because of low dependence on AIS data (in dynamic attributes) when AIS status was not "moored" at the given ports. In Figure 10, this effect can be observed in various ports in Gulf of Mexico and Atlantic coast where a range of AIS messages appear at the sea, leaving the port, reaching the port, and approaching the terminal. To fix this effect, polygons could be used to represent other ports and AIS messages from those polygons could be removed.

CONCLUSION

Container terminals play a vital role in connecting maritime ports to vessels for global supply chains. Using deep learning and AIS data is not explored widely when it comes to optimize cargo handling, especially in combination with queuing and scheduling. This study has discussed the selection of reasonable deep learning model and optimization of hyper parameters. This study has explored various forecasting approaches to reach high forecast accuracy. It is observed that complex models are not needed to increase prediction accuracy. More detailed data is needed about the port for further improving prediction accuracy, such as, tug boat activities, pilot guiding process, and navigation process. Weather conditions also affect the trajectories and speed of vessels through sea current and crosswinds. Hence, it is worth considering weather data to improve the forecasting accuracy.

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