



Leveraging machine learning and optimization models for enhanced seaport efficiency

Mahdi Jahangard¹ · Ying Xie² · Yuanjun Feng³

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Abstract

This study provides an overview of the application of predictive and prescriptive analytics in seaport operations and explore the potential of integrating predictive outputs into prescriptive analytics to advance research in this field. A systematic review of 124 papers was performed to identify and classify key topics based on application areas, types of applications, and employed techniques. Our findings show a growing interest in developing either predictive or prescriptive analytics models to improve seaport operational efficiency. However, there is limited research combining predictive outputs with prescriptive analytics for data-driven decision-making. Additionally, the hybridization of machine learning and operations research techniques remains underexplored. One promising area is applying machine learning models, such as reinforcement learning, to solve optimization problems. Predictive maintenance and data-enabled operational control measures for port equipment and facilities are also highlighted as interesting future research areas.

Keywords Seaport operations · Port efficiency · Predictive analytics · Prescriptive analytics · Machine learning · Optimization · Systematic literature review

1 Introduction

Maritime transport is considered one of the most crucial transportation modes globally, responsible for carrying over 80% of international trade (UNCTAD 2023). This transportation mode is favored for its low cost and high-volume potential (Hu et al. 2021). However, this growing reliance on shipping has increased the demands

✉ Ying Xie
ying.xie@cranfield.ac.uk

¹ Anglia Ruskin University, Cambridge, UK

² School of Management, Cranfield University, Cranfield MK43 0AL, UK

³ Department of Operations and Supply Chain Management, Management School, University of Liverpool, Liverpool, UK



on seaports, which serve as critical logistics hubs connecting shipping with inland logistics. This heightened pressure has resulted in several challenges, such as port congestion, emissions, and operational inefficiencies. Additionally, the limited availability of land, or the high cost of expansion, further adds to the complications of such logistics hubs (Hu et al. 2021). Hence, seaports must enhance their efficiency through both internal and external actions at the operational decision level (Wu and Goh 2010).

By adopting digital technologies in ports, such as IoT, blockchain, autonomous applications, and robotics, an immense amount of heterogeneous data is generated by ports and their interconnected stakeholders (de la Peña Zarzuelo et al. 2020; Munim et al. 2020). This presents opportunities to industry and academia, to harness the power of data and unlock values in them facilitating decision-making and improving operational efficiency at ports and the wider transport system. Filom et al. (2022) identified six distinct periods in the evolution of decision-making in port operations, spanning from 1910 to the present day. These periods include scientific management from 1910 to 1945; scientific method from 1945 to 1965; management information systems from 1965 to 1970; decision support systems from 1970 to 1990; business intelligence from 1990 to 2005; and business analytics from 2005 to the present day.

Business analytics is the process of using a large amount of data from various sources, quantitative and statistical analysis, and explanatory and predictive techniques, to gain insight and foresight for supporting decision-making by actions and decisions based on facts and data (Davenport and Harris 2007). To accomplish this, business analytics utilize various methods from data science, machine learning (ML), and operations research (OR) which are categorized into three phases; namely, descriptive, predictive, and prescriptive analytics (Akter et al. 2019). Descriptive analytics tries to answer questions related to the past “What happened?” and “Why did it happen?”; predictive analytics tries to know about the future by answering the questions “What will happen?” and “Why will it happen?”, while prescriptive analytics seeks to answer the question “What should be done?” (Akter et al. 2019).

While descriptive analytics can provide useful hindsight information to decision-makers, predictive and prescriptive analytics hold greater significance, as highlighted by Bertsimas and Kallus (2020) and Tinoco et al. (2021). Predictive analytics leverages data-driven models, especially ML, to estimate potential decision variables based on past data. On the other hand, prescriptive analytics evaluates the impact of different actions, leading to the selection of the optimal decision-making approach, as explained by Heilig et al. (2020). For a more comprehensive understanding of various techniques for predictive and prescriptive analytics, readers may refer to Lepenioti et al. (2020).

ML, employing computational methods to learn information directly from data without depending on predetermined equations, is an important tool for business analytics, especially for descriptive and predictive applications, while prescriptive analytics usually uses OR approaches to identify optimal alternatives based on objectives and specified requirements (Barua et al. 2020). Filom et al. (2022) conducted an extensive literature review of 70 papers from 1999 to 2022 on the



application of ML techniques in port operations, revealing that 68% of the literature focuses on predictive analytics. Although ML has made considerable advancements and demonstrated promising outcomes in various areas of seaport operations, its predominant utilization is for prediction applications and cannot be applied to address all port-related challenges, particularly those of optimization problems.

In contrast, the area of OR, known as prescriptive analytics, has made crucial contributions to the solution of decision issues in the seaport sector (Zhou et al. 2021a, b). OR techniques usually determine optimum or near optimal answers to decision problems, under a set of abstraction assumptions using computer-assisted decision-making (Chong and Zak 2013). Lepenioti et al. (2020) pointed out that about 82% of the prescriptive analytics studies are related to models that have been developed based on expert knowledge. Such models are not reliable as they involve human subjectivity. To address this drawback, big data applications can help prescriptive analytics models to be less dependent on domain expert knowledge and more based on data analysis (Heilig et al. 2020). It is crucial to analyze operational data and incorporate the output into decision-making processes, to make decisions based on data, called data-driven decision-making (Heilig et al. 2020).

Although investment in port digital technologies has been expanding substantially to assist in identifying, monitoring, and aggregating required data to make more reliable and effective decisions, there are only a few literature review papers that discuss port operations from the perspective of data analytics (Heilig et al. 2020; Filom et al. 2022). Heilig et al. (2020) concentrated exclusively on data-driven decision-making within container terminals, while Filom et al. (2022) focused on the applications of ML in port operations. Therefore, there remains a gap in the literature synthesizing seaport-related issues addressed by predictive and prescriptive analytics across various terminal types within seaports, including container terminals, dry bulk terminals, liquid bulk terminals, and roll-on roll off terminals. This study conducts a systematic literature review by addressing the following research questions: (1) in which operational domains of seaports have predictive and prescriptive analytics been applied? (2) What predictive and prescriptive analytics techniques have been employed in seaport operations? (3) How can predictive and prescriptive models be integrated to enhance decision-making in seaports? Furthermore, the paper suggests possible directions for future research.

The remaining sections of the paper are structured in the following manner: Sect. 2 outlines the review methodology. Section 3 presents a systematic literature review on the utilization of predictive and prescriptive methods and their integration across various areas of seaport operations, with the findings being discussed in Sect. 4. Finally, the paper concludes with potential future research directions in Sect. 5.

2 Review methodology

A systematic literature review was carried out to synthesize research findings, identify gaps in the literature, and provide evidence-based insights to inform future research avenues. Two popular databases, namely, Web of Science (WoS)



and Scopus, were used to search literature. The most challenging step in searching relevant literature is creating a list of appropriate keywords that is both inclusive and free of irrelevant items. After multiple rounds of trial and error with various search phrases and keyword combinations, two groups of keywords were applied for predictive analytics, as shown in Fig. 1. Group (1) includes “artificial intelligent,” “neural network,” “data analytics,” and “learning,” which contains different types of learning methods such as machine learning, deep learning, and reinforcement learning, to cover ML-related methods. Group (2) entails “predic*,” “estimat*,” “forecast*” aiming to cover a wider board of predictive applications that include traditional prediction and forecasting methods. The asterisk (*) in the second group is used to expand the scope of a search and find variations of the terms; it is used only for this group as the variation of such keywords affects the search results. The third group contains “maritime terminal,” “seaport,” and “port operation” to capture port industry material which is mutual for investigating both predictive and prescriptive procedures. The fourth group contains keywords for prescriptive analytics, including “optimization,” “programming,” “heuristic,” “metaheuristic,” and “modelling.” To capture the overall predictive analytics side of the search query, the first and second groups were combined using the OR operator. Then, the new group and the third group are combined using the AND operator as a final search query, to ensure the papers reflect predictive analytics to seaport operations. To make a final search query for prescriptive analytics in port operations, the third and fourth groups were mixed using the AND operator. The words within each group are combined by the OR operator.

Figure 1 presents an overview of the paper selection process. A search query is applied in the “title, abstract, keywords” of Scopus and WoS to gather

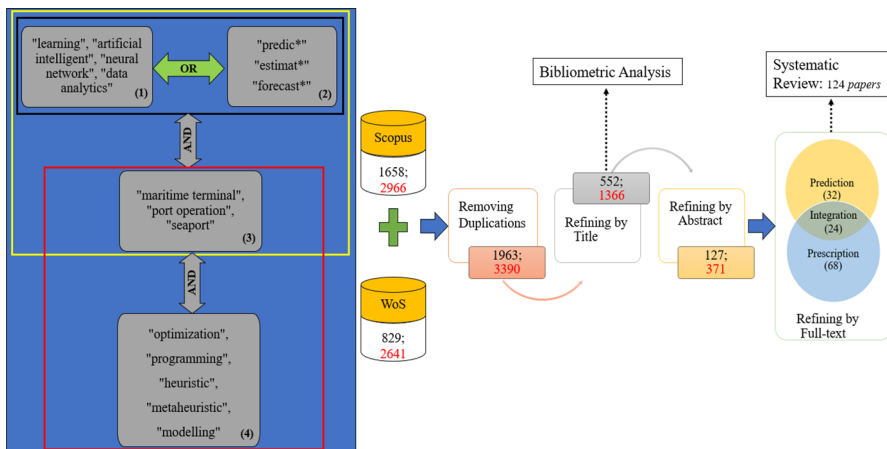


Fig. 1 The procedure of selecting papers. NB: The number of articles for predictive models is in black color, and the number for prescriptive models is in red color. “(Group (1) OR Group (2)) AND Group (3)” constitute the final search query for predictive analytics in port operations. “Group (3) AND Group (4)” constitute the final search query for prescriptive analytics in port operations



relevant English research journals and conference papers (books and book chapters excluded) for a period ending up to the end of 2022.

Prescriptive-related papers, collected from both databases, are more than the predictive ones. Scopus yielded 2966 for the former and 1658 for the latter, while WoS yielded 2641 and 829 in the same row. Before any filtering, the duplicates were removed, resulting in 1963 and 3390 papers for predictive and prescriptive applications, respectively. Then, three steps were taken to curate a selected set for systematic literature review. Firstly, they were refined by title, for us to understand the main topic, reaching 552 and 1366 papers for predictive and prescriptive applications, respectively. Secondly, by reviewing abstracts, we selected predictive and prescriptive papers related to port operations only, therefore some areas such as shipping and supply chain were excluded, resulting in 127 and 371 papers for prediction and prescription applications, respectively. As a final step, the full text of the remaining papers was reviewed from various perspectives, including their objectives, methods, quality, and scope. This ensured comprehensive coverage of port operations in the systematic literature review, with the papers categorized into three classes: Predictive models, Prescriptive models, and Integration of both models.

Regarding prescriptive models, as traditional OR methods play a crucial and long-lasting role in the optimization of seaport operations, especially in container terminals, there exists a vast number of articles pertaining to OR in seaport operations. Although reviewing traditional OR methods is not related to data-driven decision-making, to have an inclusive insight into their application at seaports, we briefly reviewed some of them. To ensure the selection of mainstream and high-quality articles for prescriptive analytics, a set of criteria was applied: (1) articles focusing on various types of seaport terminals were selected and (2) for articles on container terminals, only those published after 2008 were selected, given the existence of a review paper (Stahlbock and Voß 2008). In contrast, owing to a scarcity of relevant papers, no specific selection criteria were applied to restrict the number of articles concerning predictive analytics. In addition, all the papers employing both predictive and prescriptive analytics simultaneously were selected and classified under the label of Integration. For the systematic literature review, a total of 124 papers were selected, comprising 68 focused on predictive applications, 32 on prescriptive applications, and 24 addressing their integration in seaport operations.

3 Predictive and prescriptive analytics in seaport operations

Port operators need to optimize their operations and resources, reducing costs and increasing efficiency by making proper decisions while handling growing cargo volumes (Kizilay and Eliyi 2021). Modern real-world decision-making systems often contain predictive and prescriptive analytics. While predictive analytics focuses on projecting what will happen in future or estimating unknown parameters, prescriptive analytics involving operational research methodologies is often applied to find the best optimization alternative(s), or achieve multiple objectives under a set of constraints (Lepeniotti et al. 2020). However, since the value of some parameters of the optimization model is unknown, estimating them by



predictive models, especially ML, and inputting them into the optimization model can improve model performance.

In general, seaport operations can be distinguished between landside and seaside operations, as shown in Fig. 2 (Wei et al 2020). The type of landside operations depends on the types of cargo handled and the characteristics of the ships. Generally, seaports can be classified into four categories, that is, lift-on lift-off container terminals, roll-on roll-off (Ro-Ro) vehicle terminals, liquid bulk terminals, and dry bulk cargo terminals. Figure 2 shows the seaside and landside operations at lift-on-lift-off container terminals. Although seaside operations are almost the same for all types of terminals, landside operations vary with the type of terminal. In Fig. 3, landside operations in other types of terminals, i.e., liquid bulk, dry bulk, and Ro-Ro, are presented.

To provide a more organized review of predictive and prescriptive analytics applied in seaport operations, we classified reviewed papers into three application areas: *Demand forecasting*, *Landside operations*, and *Seaside operations*. While *Demand forecasting* may not be extensively discussed in the context of seaport operations (Yang et al. 2019), we consider it under predictive analytics due to its significance for port stakeholders and its impact on seaport operations. In addition, the papers integrating predictive and prescriptive models in seaport operations are represented in a separate subsection.

Landside operations are classified into *yard planning* and *transportation*, while seaside operations focus on *vessel operations* upon arrival in port.

Tables 1, 2, and 3 present a summary of the 124 reviewed articles, categorized into predictive, prescriptive, and integrated applications, respectively. Since predictive analytics utilize historical or real-time data to develop predictive models, details regarding input variables and data sources, if applicable, are presented alongside predicted variables and the methods used for such analytics in Tables 1

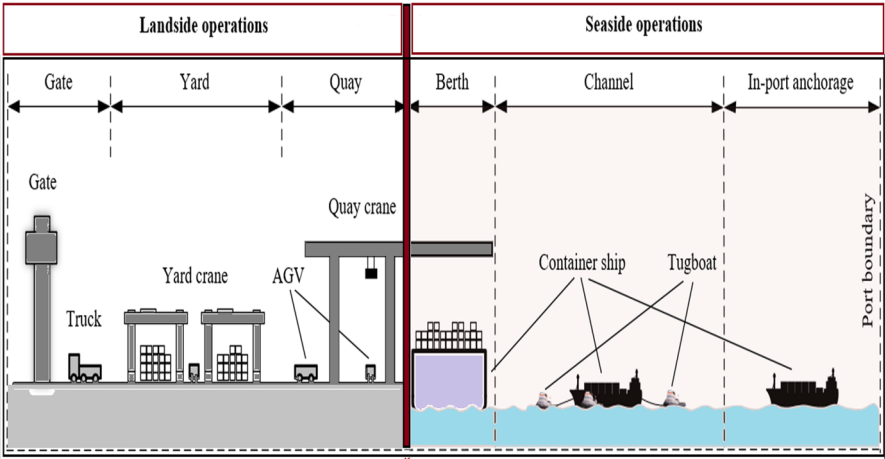


Fig. 2 Landside and seaside operations in container terminals (adapted from Wei et al. 2020)



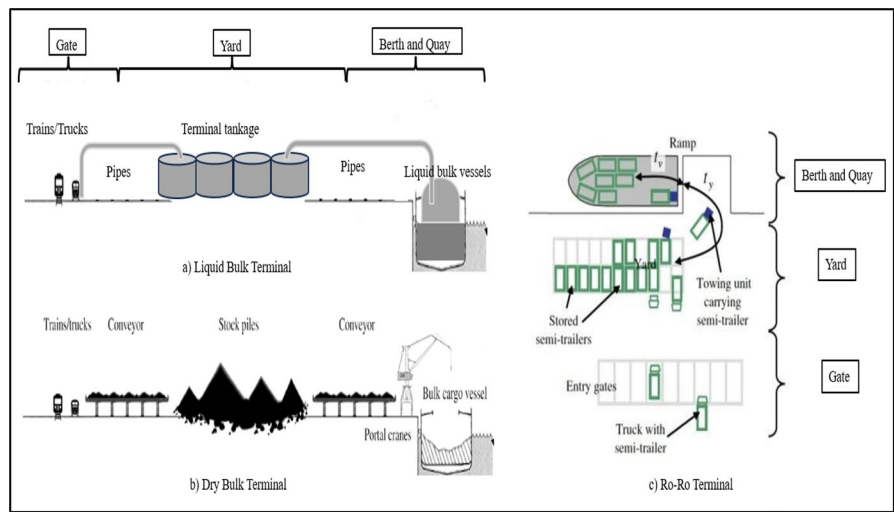


Fig. 3 Landside operations in different terminals. **a** Liquid Bulk Terminal, **b** Dry Bulk Terminal, and **c** Ro-Ro Terminal

and 3. For prescriptive analytics, the utilized methods and the type of problem are delineated in Table 2.

3.1 Predictive models for seaport operations

In this section, we review the literature on predictive models for three areas of seaport operations, namely, demand forecasting, landside operations, and seaside operations. The application of predictive analytics developed for seaport operations is summarized in Table 1.

3.1.1 Demand forecasting

Improving productivity in seaport terminals is critical, among others due to keen regional port competition. Accurate decision-making is essential in this node of the supply chain, and demand forecasting plays a significant role in port operations. Traditional techniques like time series methods often rely on linearity assumptions, whereas ML techniques can make more accurate predictions, due to their capability of exploring nonlinearity and uncertainty, particularly when working with big and unstructured data (Moscoso-López et al. 2021). However, hybrid models that combine ML and traditional models have been found to outperform individual techniques. Various predictive techniques, including traditional and machine learning models of forecasting port demand, serving different purposes, such as strategic planning for expanding container terminals (Gosasang et al. 2018; Mo et al. 2018) and port operations management (Jin et al. 2022) are summarized in Table 1.



Table 1 Summary of predictive analytics in seaport operations

References	Input variable(s)	Method(s)	Predicted variable(s)	Source of input data
Demand forecasting				
Demand forecasting using traditional methods				
Farhan and Ong (2018) and Huang et al. (2020)	Historical container throughput data	SARIMA; Classical decomposition, TBATS, seasonal dummy regression, GPM, hybrid GPM, and SARIMA	Container throughput	20 international ports ^a ; Ports of Kaohsiung, Keelung, and Taichung
Rashed et al. (2017) and Gossang et al. (2018)	Industrial confidence and economic indicators and container throughput. Economic growth rate, interest rate, inflation rate, exchange rate, population, manufacturing production index and the trade value of imports, consumer price index, fuel price, the trade value of exports, and industrial production index	ARIMA and ARIMAX; VECM	Container throughput	Antwerp port; Bangkok port
Munim and Schramm (2021) and Munim (2022)	China containerized freight index, and exogenous variables, including week-to-week change in fleet capacity, container-ship newbuilding prices, and HARPEX index	ARIMA, VAR; SARIMA, SNNAR, and TBATS	Container freight rates	Far East to North Europe, US East Coast, US West Coast, and Mediterranean routes
Demand forecasting using ML methods				
Shankar et al. (2020) and Tan et al. (2021)	Historical container throughput data	LSTM; GPM and ESN	Container throughput	Singapore Port; Busan and Singapore ports



Table 1 (continued)

References	Input variable(s)	Method(s)	Predicted variable(s)	Source of input data
Lam et al. (2004), Tsai and Huang (2017) and Jin et al. (2022)	Trade value, population, electricity demand, and GDP; interest rates, the value of export and import trade, the amount of export and import containers, and the number of quay cranes; weather and terminal operational factors like the anticipated time of vessel arrival or the number of export and import containers	NN; ANN; XGBoost	Container throughput	Hong Kong port; 10 ports in Asia ^b ; Ningbo-Zhoushan port
Demand forecasting using hybrid methods				
Xie et al. (2017), Mo et al. (2018), Ding et al. (2019) and Huang et al. (2022)	Historical container throughput data	Decomposition-ensemble and DCA; SARIMA, SVR, and BPNN; SVM and BPNN; SARIMA, LSTM, SVR, SARIMA-LSTM, and SARIMA-SVR	Container throughput	Ports of Los Angeles and Singapore; Ports of Xiamen and Shanghai; Ningbo and Wenzhou ports; Ports of Shanghai, Ningbo, Suzhou port and Lianyungang
Gökkuş et al. (2017) and Shankar et al. (2021)	Annual socioeconomic and demographic indicators, including gross domestic product, exports, and population; yearly data related to environmental, economic, and social features	(ANN-ABC and ANN-LM), MNR-GA, and LSSVM; ARIMAX-LSTM	Container throughput	Ports of Istanbul, Izmir, and Mersin; Port of Los Angeles
Landside operation				
Yard Planning				





Table 1 (continued)

References	Input variable(s)	Method(s)	Predicted variable(s)	Source of input data
Moini et al. (2012), Kouroumlioti et al. (2016) and De Armas Jacomino et al. (2021)	Container features (status, type, size), truck carrier, vessel name, date and time of arrival and departure of ship, destination, and product	DT, NB and NB-DT; ANN; OrR	Container dwell time	A port in the US; a container terminal in the Middle East; a port in Cuba
Kamal and Bae (2021)	Container weight, activity name, activity type, twin activity, yard-bay number, yard coordinates, and processing time for each activity	AMR and AMAR	Loading/unloading time	Busan port
Transportation				
Xie and Huynh (2010)	Number of truck drop-offs and pickups and containers loaded and discharged	SVM and GPM	Daily truck trips	Huston port
Kim et al. (2021)	Container movements (loading, discharging, importing, and exporting) and equipment (yard trucks and container cranes) and accidents	DNN, GB, and RF	Accident occurrence	Busan port
Nadi et al. (2021)	Truck volume	FFNN	Truck traffic	Rotterdam port
Li et al. (2022a, b)	Vessel-related information, arrival weekdays, and weather conditions	GRU and FCNN	Truck arrivals	A container terminal in Southern China

Table 1 (continued)

References	Input variable(s)	Method(s)	Predicted variable(s)	Source of input data
Seaside operations				
Štepec et al. (2020), Bakar et al. (2022), Abreu et al. (2022) and Atak et al. (2022)	Vessel features, amount and the type of the loaded and unloaded cargo, exact times of arrival and departure, weather and tidal; time of arrival, type of the ship, size of the ship, mode of operation, index capacity, berthing duration; geography, operation, and stay time data; temperature, wind, and humidity	GB; ANN, MLP, RF, DT, and XGBoost; DT and RF; Ridge, LASSO, SVR, and RF	Vessel turnaround time	Bordeaux port; Port of Aalborg; Brazilian ports; a container terminal in Turkey
El Mekkaoui et al. (2022)	Navigational data from AIS, vessel particulars, weather information, and port data for actual arrival time	MLP, CNN, and RNN	Vessel arrival time	Bulk port in Morocco
Liu et al. (2020)	AIS Data	K-means	Channel capacity	Tianjin Port
Chatterjee and Cho (2022)	Data related to the type and number of unloaded containers	SVM, KNN, and trees ensemble	Vessel size	Busan port

The semicolon (':') is used to separate the methods and sources utilized for each reference within the same row

^aPorts of Antwerp, Buenos, Busan, Callao, Durban, Hamburg, Hong, Jeddah, Kaohsiung, Long, Los, Melbourne, New, Rotterdam, San, Santos, Shanghai, Singapore, Veracruz, and Yokohama

^bPorts of Shanghai, Singapore, Hong, Shenzhen, Busan, Kaohsiung, Yokohama, Kobe, Nagoya, and Keelung





Table 2 Summary of prescriptive analytics in seaport operations

References	Method(s)	Problem(s)
Landside operations		
Yard Planning		
He et al. (2010), Zheng et al. (2019), Guo et al. (2021a, b) and Li et al. (2022a, b)	GA; GA; MIP; MIP	Material handling equipment planning problem, e.g., yard crane, gantry crane, multiple gantry cranes
Bazzazi et al. (2009), Jiang et al. (2013), Hu et al. (2014), Lin and Chiang (2017), Zhou et al. (2020), Mar-Ortiz et al. (2020), Hu et al. (2021) and Chen et al. (2021)	GA; MIP; Heuristic; Heuristic; Simulation and MIP; TS; NSGA-II; Heuristic	Space allocation problem
Bian et al. (2015), Güven and Türsel Eliyi (2019), Feng et al. (2020), Feng et al. (2022) and Azab and Morita (2022)	DP; Simulation; SP; DP; ILP	Container relocation problem
Cordeau et al. (2015), Hottung and Tierney (2016), Jovanovic et al. (2017), Parreño-Torres et al. (2019), Bisira and Salhi (2021) and Boge et al. (2020)	Simulation; GA; GrA; ILP; BLP; MIP	Pre-marshaling problem
Transportation		
Al-Khayyal and Hwang (2007), Keceli (2016), Xie et al. (2018), Hu et al. (2019), Li et al. (2020) and Gharehgozli et al. (2022)	MIP; Simulation; DP; PSO; ILP and NSGA-II; SA	Scheduling problem
Heilig et al. (2017), Abdelmagid et al. (2021) and Zhang et al. (2022)	SA; BLP; RL	Truck routing problem
Yang et al. (2018a, b), Jeon et al. (2011), Zhong et al. (2020), Hu et al. (2022) and Yue and Fan (2022)	GA; RL; MIP; RL; RL	AGV routing problem
Seaside operations		
Arango et al. (2011), Nishi et al. (2020), Bacalhau et al. (2021), Barros et al. (2011), Robenek et al. (2014), Jos et al. (2019), Park et al. (2021), Liu et al. (2021a), Liu et al. (2021b), Liu et al. (2022), Zhen et al. (2017), Wei et al. (2020), Yıldırım et al. (2020), Golias et al. (2014)	GA; DP; GA; MIP and SA; MIP; MIP; PSO; MIP; MIP; MIP; ILP; MIP; Simulation; Heuristic	Berth allocation problem

Table 2 (continued)

References	Method(s)	Problem(s)
Lee et al. (2008), Zeng and Yang (2009), Chung and Choy (2012), Lv et al. (2020), Yassen et al. (2021), Safaeian et al. (2021)	GA; MIP; SA; TS; TLBO; Simulation	Quay crane allocation problem
Yue et al. (2021), Nehme et al. (2021), Kaveshgar and Huynh (2015), Yu et al. (2022a, b), Chargui et al. (2021a), Nourmohammadzadeh and Voß (2022), Cho et al. (2021), Al-Dhaheri et al. (2016) and Yu et al. (2022a, b)	MIP; ILP; MIP and GA; MIP; VNS; MIP and SA; Heuristic; GA; MIP	Integrated quay cranes allocation problem with AVGs, yard cranes, yard truck, berth allocation





Table 3 Summary of the integrated predictive and prescriptive analytics in seaport operations

References	Prediction method(s)	Input variable(s) for prediction	Predicted variable(s)	Optimization problem(s)	Optimization method(s)
Predict_then_optimize					
Landside operations					
Kang et al. (2006), Gaete et al. (2017), Maldonado et al. (2019), Cho et al. (2022) and Park et al. (2022)	NB and DT; NB, OneR, ZeroR, and K*; RF; GMM	Truck company; container features, the origin port, and consignee; dispatching type, dispatch consignee, month and port of origin; arrival and departure time	Weight groups of export containers; container dwell time; weight groups of export containers	Space allocation problem	SA; Simulation; Simulation; Online optimization
Chen et al. (2013), Caballini et al. (2020) and Nadi et al. (2022)	QM; CA; NN	Arrival time of trucks; container features; traffic data, network graph, vessel arrival time, and container discharge time	Arrival time and queue length of trucks; container grouping; Truck traffic	Scheduling problem	GA; MIP; GA
Seaside operations					
Jin et al. (2004), Guo et al. (2021a, b), Kolley et al. (2021, 2022) and Xiang and Liu (2021b)	NN; ANN; DT and ANN; LR, ANN, DT, and KNN; K-means	Import containers; AIS data; weather conditions; arrival time	Import containers; vessel handling time; vessel arrival time; operation time	Berth allocation problem	GA; MIP; MIP; MIP; MIP
Xiang and Liu (2021a) and Yu et al. (2018)	K-means; RF	Container volume, arrival time; ship features, and route type	Operation time; vessel arrival time	Integrated quay cranes and berth allocation problem	RO; Simulation
Chargui et al. (2021b)	ANN-VNS	Container type, equipment failure rate	Productivity rate of quay cranes	Quay crane allocation problem	MIP
Fancello et al. (2011), Yan et al. (2021), Yan et al. (2022a, b) and Yan et al. (2020)	NN; XGBoost; KNN; RF	Ship features, number of workers required, ETA month, weekday, and hour	Vessel arrival time; ship deficiency number	Port state control officers scheduling	ILP; ILP; SP; ILP
Hybridized techniques					

Table 3 (continued)

References	Prediction method(s)	Input variable(s) for prediction	Predicted variable(s)	Optimization problem(s)	Optimization method(s)
ML in OR					
Hottung et al. (2020)	DL	Feasible solutions	Lower bound	Container pre-marshalling problem	Tree search
Zhang et al. (2020)	RF	Feasible solutions	Upper bound	Container relocation problem	Tree search
Cheimanoff et al. (2021)	RF	Feasible values	Hyperparameter	Berth allocation problem	RVNS
OR in ML					
Milenković et al. (2021)	FNN	Container traffic	Container flow	Optimize the structure of FNN	GA, SA



3.1.1.1 Demand forecasting using traditional methods Rashed et al. (2017) compared several univariate time series models to predict container throughput at the Port of Antwerp. Their approach incorporated industrial confidence—a crucial metric assessed by factors such as production expectations, current orders, and stock levels in the industrial sector. According to their results, the autoregressive integrated moving average intervention model (ARIMAX) was the most accurate for 20 years of analysis. Gosasang et al. (2018) developed a vector error correction model (VECM) to forecast container throughput for export and import containers in Bangkok, with the aim of planning future expansion of terminal infrastructure. In another study, the seasonal autoregressive integrated moving average (SARIMA) model was developed for container throughput, to maintain the competitiveness of the port, through the appropriate short- and mid-term strategies (Farhan and Ong 2018). Huang et al. (2020) compared the forecasting performance of six univariate methods, namely classical decomposition, trigonometric box-cox trend seasonality (TBATS), regression model with seasonal dummy variables, gray model, hybrid gray model, and SARIMA. The latter was found to be a dependable forecasting technique based on monthly data of container throughput in three ports in Taiwan (Keelung, Kaohsiung, and Taichung).

Container freight rates is another important indicator influencing port operations. To predict this indicator, Munim and Schramm (2021) applied ARIMA, artificial neural network (ANN), and vector autoregressive (VAR), the latter outperforming the former two. Munim (2022) employed three seasonal forecasting models, namely SARIMA, seasonal neural network autoregression (SNNAR) and TBATS. The results showed that combination of TBATS and SARIMA outperforms SARIMA and SNNAR as well as their combination.

3.1.1.2 Demand forecasting using ML methods Concerning ML methods, Lam et al. (2004) developed a neural network (NN) to predict cargo throughput in Hong Kong. Tsai and Huang (2017) proposed an ANN model to predict the container flows between major ports simultaneously. The results of experiments showed that prediction errors were small compared to traditional methods. Shankar et al. (2020) forecasted container throughput in Singapore using long short-term memory (LSTM) which achieved better performance than traditional models. Tan et al. (2021) investigated two ML-based prediction models, namely gray prediction model (GPM) and echo state network (ESN) to forecast container throughput. ESN provided more accurate results in larger samples, in the case of container throughput data of Busan and Singapore ports.

From an operational planning perspective, Jin et al. (2022) introduced an extreme gradient boost (XGBoost) model to predict the daily export and import containers destined for Ningbo Zhoushan Port. However, the researchers did not forecast a few days ahead, which would allow for more effective operations and consideration of the impact of major disruptions.

3.1.1.3 Demand forecasting using hybrid methods Researchers have used a combination of historical and ML methods to improve the accuracy of prediction mod-



els of demand forecasting. Xie et al. (2017) developed a novel decomposition-ensemble approach to forecast container throughput. The employed different data characteristic analysis (DCA) methods, including X12-ARIMA, empirical model decomposition (EMD), and classical decomposition (CD) to analyze components like seasonality, mutability, stationarity, and complexity of the data. Their empirical analysis, using data from Los Angeles and Singapore, showed that the DCA-based hybrid approach outperformed other methods. Gökkuş et al. (2017) compared different hybrid forecasting models such as artificial neural network with artificial bee colony and Levenberg–Marquardt algorithms (ANN-ABC and ANN-LM), multiple nonlinear regression with genetic algorithm (MNR-GA), and least square support vector machine (LSSVM), for container traffic in three main Turkish ports (Istanbul, Izmir, and Mersin). Results displayed the reliability of the LSSVM model compared to the ANN models.

Mo et al. (2018) introduced a group method of data handling (GMDH) to forecast container throughput based on linear pattern and nonlinear variation. A joint model combining support vector machine (SVM) and BPNN model was proposed to forecast container volume (Ding et al. 2019). The results, based on yearly data from Ningbo and Wenzhou, showed that the proposed model outperforms the single models. Furthermore, Shankar et al. (2021) proposed a hybrid model of ARIMAX-LSTM to forecast container demand. The model outperformed the ARIMAX, LSTM, and VAR ones, on data from the Los Angeles port. Huang et al. (2022) examined hybrid models for forecasting container throughput under covid-19. The empirical results showed that the hybrid model of SVR-LSTM outperforms single models and the longer the horizon of the training dataset, the better the performance of the model.

Summary of demand forecasting: Overall, the review of the literature on demand forecasting shows that various prediction techniques and different datasets have been used to evaluate the accuracy of forecasting models. Hybrid models, integrating machine learning and traditional methods, show better performance than others, with a capability of identifying linearity and non-linearity variations. In addition, although only around 16% of the seaborne cargoes of the world was containerized in 2022 (UNCTAD, 2023) most prior research has focused on containerized freight and there is a lack of studies for other types of seaport terminals. There is also a trend to consider various exogenous factors in demand forecasting (Tsai and Huang 2017), including political events, economic factors, weather, inventories, and other external characteristics.

3.1.2 Predictive models for landside operations

Landside activities for import containers begin with transporting the container from quayside, storing it in the stacking yard and finally releasing the container through the gate (Ting et al. 2010), while for exports, the process is reversed (Mar-Ortiz et al. 2020; Rodrigue and Notteboom 2006). Landside operations include loading and unloading, storage, internal transport, gate operations, and hinterland transport. As such, this is usually considered as a combinatorial



optimization problem. Given their evident link, we classified landside operations into two components: yard planning and transportation (Zhang et al. 2020).

3.1.2.1 Predictive models for yard planning To improve the efficiency and productivity of the yard area in ports, estimating performance indicators are of great importance to decision-makers. Long dwell times of containers are known as one of the key performance indicators affecting yard operations, fuel consumption and congestion, resulting in the inefficiency of container terminals (Moini et al. 2012). Dwell time prediction appears to be one of the most prominent research topics in yard planning. The reviewed papers related to predictive models of yard planning are summarized in Table 1.

Container dwell times can be affected by a number of factors concerning the features of the containers, stakeholders, and terminal policies. Moini et al. (2012) employed three methods, namely naive Bayes (NB), decision tree (DT), and an NB-DT hybrid to estimate container dwell times based on a set of determinants related to the features of containers, trucks and vessels. The results show the DT outperforms the others. Kourounioti et al. (2016) applied ANN to predict container dwell times. The results demonstrated that the day and month of discharge, the port of origin, the size and type of container, and the type of cargo are determinants of import container dwell time. In another study, De Armas Jacomino et al. (2021) proposed an ordinal regression (OrR) approach to estimate the dwell time for import containers and identified relevant features, such as days in the country, arrival weekday, arrival month-day, destination, and product, as determinants of dwell time estimation. Kamal and Bae (2021) used adversarial multivariate regression (AMR) and adversarial multivariate auto-regression (AMAR) to predict the time required to load and unload containers.

3.1.2.2 Predictive models for transportation Transport operations are an indispensable part of container terminals linking the seaside and landside (Blumhagen 1981). Terminal transport operations regard the scheduling and routing of equipment such as trucks and automated guided vehicles (AGV), aiming to optimize port costs, responsible for a significant share of port-related traffic (Heilig et al. 2017). Although the transportation problem is usually considered as one of prescriptive analytics, a few studies have focused on predicting truck traffic. These are summarized in Table 1.

Xie and Huynh (2010) deployed support vector machine (SVM) and Gaussian process (GaP) models to predict daily truck trips at the port of Houston. Results showed that the two models outperformed the multilayer feedforward neural network (MLFNN) model when tested on a dataset that included the number of truck drop-offs and pickups, along with the number of containers loaded onto and discharged from trucks. Furthermore, Nadi et al. (2021) proposed a feedforward neural network (FFNN) to predict the hourly outbound truck traffic at the port. Li et al. (2022a, b) proposed a hybrid model of a gated recurrent unit and fully connected neural network (GRU-FCNN) to predict truck arrival times in container terminals, considering the impact of weather, weekday, and ships' arrival and departure times.



To predict accident occurrence rate related to trucks in Busan port, Kim et al. (2021) applied three ML methods, such as DNN, gradient boosting (GB), and RF. The first two methods were more accurate based on container movements (loading, discharging, importing, and exporting) and equipment (e.g., yard trucks and container cranes) and accidents, but a lack of data on other factors, such as accident type, cause, and time of incidence, could also have had a significant impact on the occurrence of accidents.

Summary of predictive models for landside operations: The utilization of predictive analytics in landside operations, specifically within the realms of yard planning and transportation, holds the potential to substantially enhance operational efficiency in seaports. Predictive models applied to yard planning principally entail the prediction of container movements inside the port, including the forecasting of container dwell times. Moreover, predictive models of terminal internal transport are focused on forecasting variables, such as traffic patterns and congestion levels. These applications collectively contribute to the optimization of seaport operations through proactive decision-making.

3.1.3 Predictive models for seaside operations

As shown in Fig. 2, seaside operations in seaports are associated with vessel operations, including navigation and maneuvering inside the port, aided by towage operations, berthing and unberthing, involving line handling at berth and anchorage management. Activities related to vessels affect subsequent terminal operations and their efficiency. Therefore, applying accurate prediction models at seaside activities may improve the whole efficiency of ports. Table 1 summarizes predictive models for vessel operations of the reviewed papers.

Vessel arrival time: El Mekkaoui et al. (2022) employed three deep learning methods, namely multilayer perceptron (MLP), RNN, and convolutional neural networks (CNN) to predict the arrival time of ships in a bulk port in Morocco. Based on data from four different sources, including automatic identification systems (AIS), vessel particulars database, weather information, and port data, their results showed that the last two models outperformed the MLP model. Liu et al. (2020) applied k-means clustering for different types of ships entering and leaving the port to estimate the navigable capacity of the Dagusha channel of Tianjin port, based on one-month AIS data, which apparently affects arrival times.

Vessel turnaround time: Another important performance indicator in seaside operations, affecting the efficiency and capacity of the port, is vessel turnaround time, including cargo handling time at berth and waiting for berthing. Štepec et al. (2020) employed a gradient-boosting model based on the DT technique to predict vessel turnaround time, considering vessel features, available berths, and external data (weather, tides, etc.). Compared to the existing manual system, the results of the proposed model were more accurate. To facilitate planning investment and installation of cold ironing, Bakar et al. (2022) forecasted ship berthing time using various methods, including ANN, multiple linear regression (MLR), RF, DT, and XGBoost. ANN showed the best performance based on input variables, including time of arrival, type of the ship, size of the ship, mode of operation, and ship capacity. In



addition, Atak et al. (2022) investigated the impact of weather on the handling time of containers at berth, through ML-based regression techniques, such as Ridge, LASSO, SVR, and RF with fuzzy C-means clustering. Their findings indicated that wind speed affected vessels' port stay, and the best prediction was achieved by an RF model with two-cluster fuzzy dummy variables. Abreu et al. (2022) applied a DT and RF model to predict ship turnaround times based on features of cargo, geography, operation, and stay time. The RF model showed better performance by considering geographical and cargo features.

Vessel size: Chatterjee and Cho (2022) developed ML methods, including SVM, KNN, and tree ensemble learners, along with neighborhood component analysis, to estimate vessel size based on the number of containers on-board for unloading and the number of export containers to be loaded, in order to allocate the optimum number of quay cranes. Linear support vector machine (LSVM) provided more accurate results.

Summary of predictive models for seaside operations: the development of predictive models for seaport operations is intricately linked to vessel-related parameters, encompassing variables, such as arrival time, turnaround time, and vessel size. These predictive models are designed with the overarching objective of augmenting the overall efficiency of seaport operations.

3.2 Prescriptive models for seaport operations

In this section, we examine existing literature concerning prescriptive models applied to landside and seaside operations in seaports. The application of prescriptive analytics developed for seaport operations is summarized in Table 2.

3.2.1 Prescriptive models for landside operations

We discuss prescriptive models for landside operations encompassing both yard planning and internal terminal transport.

3.2.1.1 Prescriptive models for yard planning From an operational point of view, yard planning primarily consists of two parts; handling equipment planning and cargo handling (Zhang et al. 2020). The planning of equipment is associated with scheduling and assigning decisions, whereas cargo handling focuses on optimizing cargo issues, such as the storage allocation problem (Mar-Ortiz et al. 2020), the pre-marshaling problem (Bisira and Salhi 2021), and the container relocation problem (Feng et al. 2020). Appropriate yard planning can lead to the high productivity of port operations. The main aim of prescriptive analytics here is to minimize unproductive container movements (i.e., relocating, pre-marshaling) and crane movements under some restrictions on container retrieval sequence, and safety like slot weight and heavy-over-light limitations (Carlo et al. 2014). A summary of reviewed prescriptive models for yard planning is presented in Table 2.

Handling equipment planning: This refers to planning equipment for operations in storage yards to enhance the overall efficiency and productivity of seaport



terminal operations. He et al. (2010) minimized the total time of yard crane movement between blocks and delayed workloads while Zheng et al. (2019) minimized the total tardiness of retrieval tasks by single-yard crane scheduling under uncertainty. In addition, while Guo et al. (2021a, b) scheduled gantry cranes for container movement in the yard, the integration of multiple gantry cranes and trucks was discussed by Li et al. (2022a, b).

Space allocation problem: This task involves determining where to place cargo in the storage yard to maximize space utilization, minimize handling costs, and ensure efficient cargo retrieval when needed. The space allocation problem has been investigated for import containers (Bazzazi et al. 2009; Lin and Chiang 2017), export containers (Hu et al. 2014), workload assignment problem between blocks (Mar-Ortiz et al. 2020), and Ro-Ro terminals (Chen et al. 2021). Moreover, some studies have addressed this problem by considering a flexible strategy for sharing storage at trans-shipment ports (Jiang et al. 2013; Hu et al. 2021), integrating yard space allocation problem, block assignment to vessels and yard crane allocation (Zhou et al. 2020).

Container relocation problem: This refers to the unproductive operation of moving blocking containers when retrieving. This problem was examined in different studies, e.g., minimizing the number of container relocations (Bian et al. 2015; Feng et al. 2020), considering the trade-off between the number of container relocations and truck turnaround time (Feng et al. 2022; Azab and Morita 2022), and incorporating operational constraints, such as weight in this problem (Güven and Türsel Eliyi 2019).

Pre-marshaling problem: This involves rearranging containers in the terminal during less busy periods to ensure swift retrieval when the port experiences high traffic. Some studies have discussed the problem of minimizing such moves by different methods, e.g., simulation (Cordeau et al. 2015), genetic algorithm (GA) (Hot-tung and Tierney 2016), greedy algorithm (GrA) (Jovanovic et al. 2017), integer linear programming (ILP) (Parreño-Torres et al. 2019), mixed integer programming (MIP) (Boge et al. 2020), and binary linear programming (BLP) (Bisira and Salhi 2021).

3.2.1.2 Prescriptive models for internal transport Unlike the predictive models for transportation, prescriptive models are mainly related to scheduling and routing problems of terminal vehicles that can be addressed through not only OR methods but also ML techniques. In Table 2, there is a summary of prescriptive models for internal transport.

Scheduling problem: The primary focus here is on optimizing the timing and sequencing of tasks to improve overall efficiency and meet operational goals. Scheduling problems have been discussed with different objectives, e.g., minimizing the makespan of loading or unloading operations (Zeng et al. 2011), minimizing the expected cost of transporting and storing containers between storage yards and trains (Xie et al. 2018), minimizing terminal vehicle operating costs through the joint problem of vehicle dispatching and storage allocation of containers (Hu et al. 2019), minimizing the total delay of trains (Gharehgozli et al. 2022), balancing terminal operations with external truck activities (Li et al. 2020), improving gate



operations in multi-purpose ports (Keceli 2016), and minimizing the travel and fixed costs associated with loading and unloading of different liquid bulk products, subject to the constraints of inventory levels (Al-Khayyal and Hwang 2007).

Routing problem: This focuses on selecting the most efficient paths or routes to minimize travel time, distance, or other relevant factors. Truck routing was discussed in different studies e.g., minimizing the variable and fixed cost of trucks and emissions (Heilig et al. 2017), minimizing the truck turnaround time when they come for picking up and delivering containers (Abdelmagid et al. 2021), and applying reinforcement learning (RL) for truck routing, considering uncertainty in service times (Zhang et al. 2022). The route planning problem was also investigated for AGVs using GA (Yang et al. 2018a, b), and MIP (Zhong et al. 2020) to overcome the traffic bottleneck of AGVs. In addition, a few studies also addressed this issue using RL, to minimize the travel time of AVGs by optimizing routes on the yard side (Jeon et al. 2011), examining AGV waiting times (Zhou et al. 2021a, b), preventing conflicts among AGVs (Hu et al. 2022), and integrating path planning and scheduling of AVGs (Yue and Fan 2022). These studies emphasize how ML-based models are becoming more capable of adapting and optimizing seaport actions in real time for autonomous systems.

Summary of prescriptive models for landside operations: Overall, prescriptive models in landside operations contribute to efficient yard planning and transportation. While the former has received significant attention in minimizing container handling costs, reducing congestion, and enhancing overall operational efficiency through container allocation, stacking, and retrieval processes, the latter has been applied to optimize routing and scheduling problems in order to minimize terminal transport costs. Additionally, while ML techniques are typically employed for prediction purposes, a few studies have also utilized these techniques for routing problems as part of prescriptive analytics.

3.2.2 Prescriptive models for seaside operations

As mentioned earlier, seaside operations essentially regard the management of vessels inside the port area. Prescriptive approaches to seaside operations seek to manage vessel operations under constraints at different parts of the port, such as berth, channel and anchorage area. An overview of prescriptive models for seaside operations is shown in Table 2.

Berth allocation problem: The primary goal of the berth allocation problem (BAP) typically involves assigning each ship to a specific berth, with the aim of minimizing overall vessel turnaround time, which includes both waiting and handling times. BAP can be discussed from different angles. Some studies employed BAP to minimize the total service time of vessels in container terminals (Arango et al. 2011; Nishi et al. 2020; Bacalhau et al. 2021), and BAP was also considered in bulk ports (Barros et al. 2011; Robenek et al. 2014). While Jos et al. (2019) considered penalties for waiting time, tardiness, and benefits for early service time, Park et al. (2021) inserted into BAP a time buffer, referring to the difference between the vessel's actual arrival time and its expected arrival time. In addition, some studies have investigated the various conditions for BAP, e.g., vessel sequencing in one-way



navigation channels (Liu et al. 2021a), width channel restrictions (Liu et al. 2021b), channel planning (Liu et al. 2022), constraints of tides and channel flow control (Zhen et al. 2017), scheduling tugboats (Wei et al. 2020), priority rules for servicing vessels (Yıldırım et al. 2020), and the uncertainty of vessel arrival and handling times (Golias et al. 2014).

Quay crane allocation problem: The scheduling problem for loading and unloading containers by assigning operations to machines with the aim of minimizing vessel service time is known as quay crane allocation. The quay crane allocation and scheduling problem, aiming at minimizing vessel turnaround times have been investigated with different methods such as GA (Lee et al. 2008), GA and simulation (Zeng and Yang 2009; Chung and Choy 2012), MIP (Lv et al. 2020), simulated annealing (SA), tabu search (TS) (Yassen et al. 2021), and teaching–learning-based-optimization (TLBO) algorithms (Safaeian et al. 2021). Other studies have focused on integrating quay cranes with other operations, e.g., AGVs (Yue et al. 2021), yard cranes (Nehme et al. 2021), yard trucks (Kaveshgar and Huynh 2015), and berth allocation (Al-Dhaheri et al. 2016; Cho et al. 2021; Chargui et al. 2021a; Yu et al. 2022a, b; Nourmohammadzadeh and Voß 2022; Yu et al. 2022a, b).

Summary of prescriptive models for seaside operations: In summary, prescriptive models have approached seaside operations from diverse angles, considering different objective functions and addressing various constraints, such as vessel sequencing, channel restrictions, and weather conditions. Additionally, a range of methods have been employed to solve such seaside problems.

3.3 Integration of predictive and prescriptive models

Numerous predictive models, particularly those utilizing ML techniques, are readily accessible to port operations. However, such models have yet to be integrated into prescriptive methods that aid decision-making. Meanwhile, multiple prescriptive models have been implemented in port environments without harnessing the valuable insights produced by predictive models. The incorporation of predictive and prescriptive models brings significant advantages as it empowers organizations to make well-informed and precise decisions ahead of time. Through an analysis of relevant literature, we have categorized the integrated prediction and prescription models into two main categories: *predict_then_optimize* and *hybridized techniques*, which are summarized in Table 3.

3.3.1 Predict_then_optimize

This integration aims to furnish tailored and specific solutions by leveraging vast datasets, thereby capitalizing on the wealth of available data (Lepeniotti et al. 2020). Given the intricate nature of both predictive and prescriptive methods, a common practice for their integration involves the paradigm of a sequential two-stage structure known as *predict-then-optimize* (PO) (Yan and Wang 2022). In essence, key unknown parameters of optimization problems are first predicted by predictive models, aiming to minimize prediction error, measured by different



metrics such as mean square error (MSE), mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). Consequently, the downstream optimization model, utilizing prediction output for these unknown parameters, is resolved. A few studies that effectively integrate predictive outcomes with prescriptive methods in seaports are reviewed below based on their application area, namely landside and seaside operations.

3.3.1.1 Landside operations Regarding yard planning, Kang et al. (2006) applied various ML methods such as the DT and naive Bayes (NB), PART, and OneR, to classify the weight groups of export containers based on features like truck company, weight announced in advance, and type of container. They, then, developed an SA for the stacking problem. The results showed that the number of rehandling of containers is reduced effectively. Gaete et al. (2017) compared several classification algorithms such as K-nearest neighbors (KNN), NB, OneR, ZeroR, and K* to identify different classes of container dwell time and then applied a simulation model to assign space to import containers based on predicted dwell time. Maldonado et al. (2019) predicted the dwell time of containers through the RF method and applied simulation to address the container stacking problem, considering the assigning block and determining the container's location based on the predicted outputs. To apply an online optimization model for stacking export containers, a Gaussian mixture model (GMM) was first applied to classify the export containers into proper weight groups (Park et al. 2022; Cho et al. 2022).

In terms of transportation at ports, Chen et al. (2013) proposed a three-stage approach to mitigate truck congestion at the gate, including employing probability distribution functions to predict the arrival time of trucks, estimating queue length using a non-stationary queue model, and applying GA to allocate the time windows. To improve truck flows in container terminals, Caballini et al. (2020) clustered import and export containers and developed a MIP model to minimize the deviation between the preferred and assigned time slot and truck turnaround time. Nadi et al. (2022) developed a graph-based neural network model to predict truck traffic variables, including volume, speed, and delay, based on a dataset of traffic data, network graph, vessel arrival time, and container discharge time in Rotterdam. Based on the prediction results, they applied non-dominated sorting genetic algorithm II (NSGA-II) to solve a scheduling problem for the departure time of trucks considering minimizing total delay time.

3.3.1.2 Seaside operations Jin et al. (2004) predicted the number of import containers through fuzzy neural networks (FNN) and applied a simulation-based genetic algorithm to minimize operational time and ship waiting time. Fancello et al. (2011) used neural networks to predict vessel arrival times. Yu et al. (2018) compared three ML-based prediction models including back propagation neural network (BPNN), classification and regression tree (CART), and RF to predict vessel arrival time based on daily data. To investigate the impact of predicted arrival times on port productivity, they applied a simulation model to allocate berths and quay cranes, resulting in improving the productivity of operations planning.



Kolley et al. (2021) predicted vessel arrival time based on AIS data and developed an MIP model to provide a robust optimization for the BAP considering a dynamic time buffer. Similarly, Kolley et al. (2022) predicted the arrival time of vessels based on AIS data through four different ML algorithms such as LR, ANN, DT, and KNN to propose a robust approach for optimizing continuous BAP while refining the dynamic time buffer, leading to reducing actual waiting time and hence enhanced service quality.

Guo et al. (2021a, b) estimated vessel handling time through ANN, considering weather conditions and applied a MIP model to solve the berth allocation problem. Chargui et al. (2021b) proposed a hybrid model of ANN, and variable neighborhood search (VNS), to predict the productivity of quay cranes based on the type of containers on the vessels and the expected equipment failure rate; then they applied the predicted rates to the quay crane scheduling problem.

Xiang and Liu (2021b) employed K-means clustering for container handling time and developed a column-and-constraint generation algorithm for the robust optimization (RO) model to minimize the deviation between expected and planned vessel berth time. Similarly, Xiang and Liu (2021a) developed a decomposition approach for the same problem while considering the integrated BAP and quay crane scheduling problem.

To enhance the safety standards of ships through maintenance plans, usually carried out at the seaside of ports, Yan et al. (2021) developed an XGBoost model to predict the number of deficiencies on ships based on 14 variables of general and dynamic ship parameters and historical inspection records, at the port of Hong Kong. Based on prediction results, an ILP model was proposed to schedule the *port state control* officers considering the maximum number of estimated deficiencies. For the same problem, Yan et al. (2022a, b) applied the KNN method for prediction and formulated stochastic programming (SP) for such a scheduling problem. In addition, to assign the port state control officers to ships based on the number of deficiencies identified by each inspector on each ship, Yan et al. (2020) proposed two approaches, integrating RF with ILP, to assign inspectors to the designated ships for inspections based on predicted deficiencies.

3.3.2 Hybridized techniques

The hybridization of OR and ML methods represents a burgeoning area of study within the OR community (Calvet et al. 2017). This approach tends to integrate ML techniques with OR methods to enhance each other's performance with increasing speed, accuracy, and efficiency. Several review papers have been published, exploring the application and challenges of hybridization across various domains (Song et al. 2019; Meisel and Mattfeld 2010; Calvet et al. 2017; Corne et al. 2012; Gambella et al. 2021; Karimi-Mamaghan et al. 2022). For example, Song et al. (2019) categorized the applications of OR in ML into data pre-processing, algorithm selection in ML, hyper-parameter tuning, model training, and clustering and ensemble learning based on optimization. This, while classifying the applications of ML in OR for metaheuristic optimization, hyper-heuristic optimization, and algorithm selection in optimization. However, the application



of hybridizing ML and OR in seaport operations is rare and it would be a fertile area for future research. We were able to find a few papers that considered this type of integration in seaport operations which are discussed below.

3.3.2.1 ML in OR Hottung et al. (2020) employed deep learning to improve the lower bounds of a tree search heuristic for finding better solutions to the container pre-marshaling problem. The experiments showed that the optimality gap for their model's solutions for cases of real-world size is less than 2%. In another study, to improve the performance of the algorithm for the container relocation problem, Zhang et al. (2020) proposed the RF method to find the upper bound by pruning the branch of the tree search based on the optimal solutions of many small-scale instances. The results showed that the model reduces significantly the average number of relocations, compared to the random selection method. Cheimanoff et al. (2021) employed the RF technique to tune the hyperparameters of a metaheuristic algorithm, called reduced variable neighborhood search (RVNS), for solving the berth allocation problem under tidal constraints in bulk terminals.

3.3.2.2 OR in ML Milenković et al. (2021) forecasted container flows, namely total container traffic, volumes loaded, unloaded, transit, and empty containers, through the FNN method. The authors utilized two metaheuristic algorithms including SA and GA for optimizing neural network architecture. The proposed approaches perform significantly better than ARIMA according to MAE, RMSE, and MAPE metrics.

Summary of integration of predictive and prescriptive models: In summary, the integration of predictive and prescriptive analytics is applied in both seaside and landside operations to facilitate better management from the perspective of *predict_then_optimize* and hybridized techniques. While the former provides seaport authorities with a holistic approach to decision-making, enabling them to make better-informed decisions, the latter tries to improve the quality of the solutions.

4 Discussion of findings

4.1 Areas of operations (Research Question 1)

As presented in Fig. 4, the majority of predictive analytics papers have investigated the domain of seaside operations, 38% of which aligns with the growth of technological innovation such as AIS for data collection in this domain (Yang et al. 2019). Conversely, while approximately 32% of papers studied predictive techniques for landside operations, the remaining 30% focused on demand forecasting techniques used at container terminals.

On the other hand, Fig. 5 shows the distribution of 92 prescriptive-related publications, including 68 papers investigating only prescription plus 24 integrated papers, addressing challenges in seaport operations. Prescriptive models have been





Fig. 4 Distribution of predictive applications in seaport operations (56 papers)

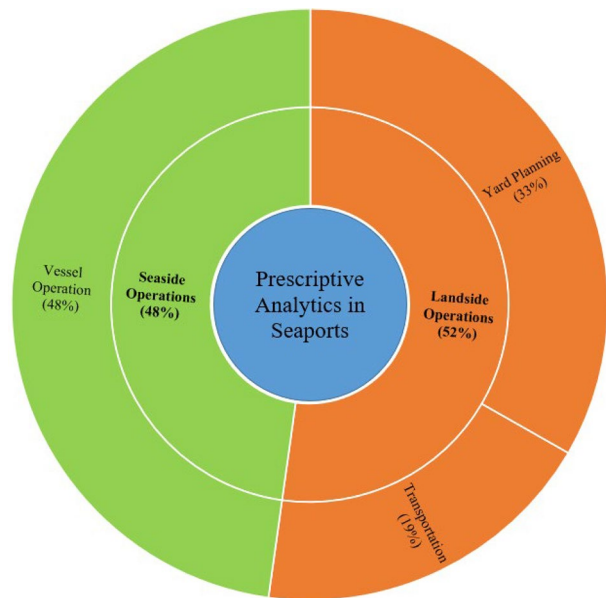


Fig. 5 Distribution of prescriptive applications in seaport operations (92 papers)

more prevalent in landside operations of seaports, comprising 52% of the reviewed papers, while the remaining 48% of papers have examined seaside operations.

4.2 Analytics techniques (Research Question 2)

Concerning predictive analytics, Fig. 6 shows the distribution of predictive techniques in seaports where ML techniques (70%) have been widely used to predict target variables, while traditional methods like time series models are responsible for only 20%. Moreover, 10% of the remaining studies applied a combination of ML and traditional methods in predictions. ANN, RF, and CNN are the most frequently used techniques of ML for prediction in the literature with around 12%, 10%, and 10%, respectively. SARIMA and ARIMA are the two most widely used techniques of traditional methods with around 4%.

As far as prescriptive analytics is concerned, shown in Fig. 7, mathematical programming constitutes 45% of the papers, with MIP being the most frequently employed technique in this category at 26%, followed by ILP at 8%. Evolutionary Computation is on the second place in prescriptive applications, with around 38%, where GA is the most popular one with 17%. Simulation and ML are two other methods for prescriptive application in seaports with around 10% and 7%, respectively. RL is the only type of ML method that has been utilized for prescriptive analysis since it has the ability to model agent-based processes that can be compared with optimization methods.

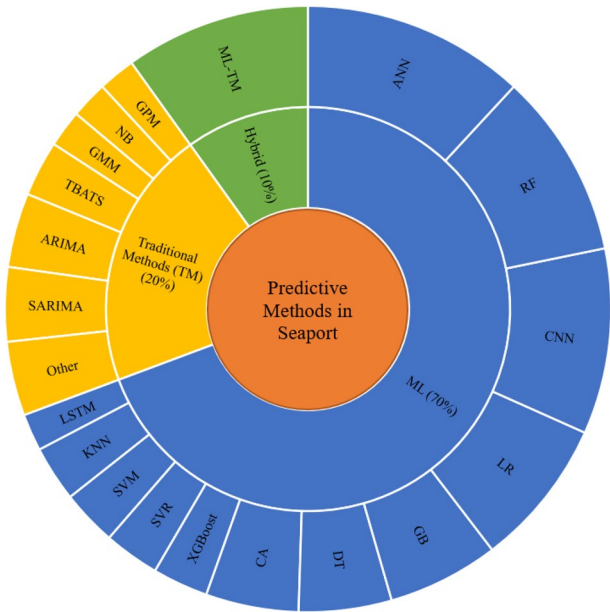


Fig. 6 Classification of papers based on predictive methods



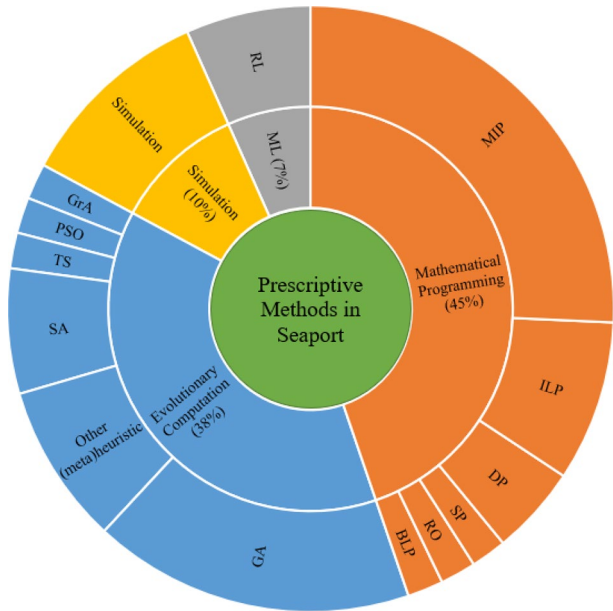


Fig. 7 Classification of papers based on prescriptive methods

4.3 Integration of predictive and prescriptive models (Research Question 3)

Based on the study overview, predictive analytics have typically been conducted using historical data from multiple sources, as shown in Table 1, while prescriptive analytics, particularly optimization methods, often make prior assumptions and model hypothetical data. However, integrating predictive and prescriptive analytics enhances one's ability to make informed and precise decisions. Integration is considered from two standpoints: predict_then_optimize and hybridized techniques. The former tries to enhance port efficiency by making good decisions through optimization, using the predicted outcomes from ML and statistical models as inputs; the latter tends to enhance the performance of models by using ML to assist OR algorithms, or using OR to tune parameters in ML. However, there are only very few studies that have integrated predictive and prescriptive models for seaport operations, as summarized in Table 3.

5 Conclusion and future research directions

By the expansion of available data, business analytics has become important to port managers, to gain enhanced insight into the future, and make data-driven decisions. Various techniques of predictive models have been discussed for demand forecasting, while predictive and prescriptive models and their integration have been examined for different operations in landside (e.g., yard planning



and transportation) and seaside (e.g., vessel operations). Our findings show that the seaside area is richer in data than the landside one, because of the existence of advanced technologies such as AIS. Consequently, the application of predictive analytics in the seaside of the port has received more attention. Integration of predictive and prescriptive models clearly presents great potential in improving seaport operational efficiency while minimizing costs and greenhouse gas emissions. Below, we offer directions for further research based on what has been accomplished and the gaps still present.

5.1 Extracting, transforming, and processing data generated from seaport operations

Data is the key to predictive analytics and data-driven decision-making. Extracting and integrating data from multiple sources within seaport terminals is essential for comprehensive analysis. Data from disparate systems, such as terminal operating systems, vessel traffic management systems, weather monitoring systems, and daily communications, such as emails, and reports, contain valuable information for business decision-making. Real-time insights from data enable operators to respond promptly to changing conditions and events. Seaport terminals generate diverse data types, ranging from structured data and unstructured data, some with spatial and temporal dependencies, available in different qualities, volumes and formats. Furthermore, integrating exogenous data sources like political factors, economic indicators, weather forecasts, and data from supply chain partners is essential for comprehensive analysis and decision-making in seaport operations. Therefore, effective handling of this data variety requires techniques capable of processing and analyzing such complexities. While existing studies focus predominantly on container terminals, which handle just under one-fifth of the world's seaborne trade, expanding the scope of the investigation not only across different types of terminals, such as dry bulk, liquid bulk, and Ro-Ro but also across various types of seaside and landside operations can be identified as a fertile area for future research.

5.2 Coordinated seaport operations

Operations within ports are characterized by extensive scope and scale. The interconnected nature of various activities within different areas of seaports highlights the way their effective integration influences overall bottlenecks and port competitiveness. For example, integrated intermodal transportation results in a number of benefits, including less traffic congestion, higher capacity utilization, and more effective cargo handling (Giusti et al. 2019). Hence, exploring coordination among various activities within seaport operations such as integrating seaside operations with landside operations and connecting landside operations with external operations can enhance overall port productivity.



5.3 Equipment fault detection and maintenance planning

There are many facilities in ports such as yard- and quay cranes on the landside and ships at the seaside that are not only expensive but have a positive effect on the efficiency of port operations. If such facilities fail to meet safety standards, the ports may face disruption and financial loss (Wang et al. 2024). It is shown that employing prediction models to detect faults in advance and proactively plan necessary maintenance and repair to prevent failures can yield encouraging outcomes (Ha et al. 2017). While a few studies applied this procedure to identify ship deficiencies and allocate the inspection resources for maintenance plans (Fancello et al. 2011; Yan et al. 2020, 2021; Yan et al. 2022a, b), Kim et al. (2021) only predicted accident occurrence rate for trucks at container terminals. However, there are a lack of relevant studies on this topic for other types of equipment at seaport, making it a fertile area for future research.

5.4 Application of reinforcement learning models in seaports

A few studies have demonstrated the potential of RL in addressing complex challenges, such as route planning for AGVs (Jeon et al. 2011; Hu et al. 2022; Yue and Fan 2022) and trucks (Zhang et al. 2022) in seaport operations. By modeling the seaport environment as a RL problem, the agent (the seaport operator) learns to make operational decisions based on various dynamic factors. RL models have the potential to be applied across multiple aspects of seaport operations to improve the efficiency, adaptability, safety, and sustainability of seaport operations by integrating autonomous systems, given that they enable continuous learning and adaptation in complex and dynamic environments (Yan et al. 2022a, b). Future research could further explore the application of RL to optimize berth allocation and vessel scheduling process, operation of cranes and other equipment, yard management, and resource (including labor) allocation (Fotuhi et al. 2013).

5.5 Integration of predictive and prescriptive models

There are two forms of integration. In the first, prediction can leverage historical data to make more effective data-driven decisions with optimization methods. As there are only a few studies that use the outcome of predictive models as inputs for optimization problems (see the first 22 papers reviewed in Table 3), integrating predictive and prescriptive analytics can be a new field for further research in port operations. However, one significant issue with this form of integration might be poor decision-making brought on by the low level of accuracy of prediction models (Yan and Wang 2022). Prediction models often focus solely on minimizing prediction errors without taking into account how these predictions will be applied and interact with subsequent optimization models. Our review identified only one study (Yan et al. 2020) that investigates the characteristics of the downstream optimization model in the prediction model. A particular loss function inspired by the structural



characteristics of the optimization problem was applied within the prediction model. Subsequently, the prediction outputs were utilized in the optimization problem. It is necessary to conduct further research on frameworks that combine prediction and optimization models for seaport operations. In the second form, integrating such techniques can lead to high-quality solutions. ML methods can enhance the performance of optimization algorithms in terms of computational complexity, while OR methods can optimize the ML hyperparameters and select the relevant features for ML methods. There are a few papers that have investigated such integration for port operations (see the last four papers in Table 3). Further research may be extended to create various hybrid paradigms for articulating and resolving optimization issues by combining the advantages of ML and OR.

6 Appendix 1: List of acronyms

Acronym	Meaning	Acronym	Meaning
ABC	Artificial bee colony	LSSVM	Least square support vector machine
AGV	Automated guided vehicle	LSTM	Long short-term memory
AIS	Automatic identification systems	MAE	Mean absolute error
ALV	Automated lifting vehicle	MAPE	Mean absolute percentage error
AMAR	Adversarial multivariate auto-regression	MARS	Multivariate adaptive regression splines
AMR	Adversarial multivariate regression	MLFNN	Multilayer feedforward neural network
ANN	Artificial neural network	MIP	Mixed integer programming
LM	Levenberg–Marquardt	ML	Machine learning
ARIMA	Autoregressive integrated moving average	MLP	Multilayer perceptron
ARIMAX	Autoregressive integrated moving average intervention	MLR	Multiple linear regression
BLP	Binary linear programming	MNR	Multiple nonlinear regression
BN	Bayesian networks	MSE	Mean square error
BPNN	Back propagation neural network	NB	Naive Bayes
CA	Clustering analysis	NLP	Non-linear programming
CART	Classification and regression tree	NN	Neural network
CD	Classical decomposition	NSGA-II	Non-Dominated Sorting Genetic Algorithm II
CNN	Convolutional neural network	OR	Operations research
DCA	Data characteristic analysis	OrR	Ordinal regression
DNN	Deep neural network	PO	Predict-then-optimize
DP	Dynamic programming	PSO	Particle swarm optimization
DT	Decision tree	QM	Queue model
EMD	Empirical model decomposition	RF	Random forest
ESN	Echo state network	RL	Reinforcement learning



Acronym	Meaning	Acronym	Meaning
ETA	Estimated time arrival	RMSE	Root mean squared error
ET	Extra trees	RNN	Recurrent neural network
FCNN	Fully connected neural network	RO	Robust optimization
FFNN	Feed forward neural network	RVNS	Reduced variable neighbourhood search
FNN	Fuzzy neural network	SA	Simulated annealing
ILP	Integer linear programming	SARIMA	Seasonal autoregressive integrated moving average
IoT	Internet of things	semi-SPO	Semi-smart predict then optimize
KNN	K-nearest neighbors	SNNAR	Seasonal neural network autoregression
GA	Genetic algorithm	SP	Stochastic programming
GrA	Greedy algorithm	SVM	Support vector machine
GaP	Gaussian process	SVR	Support vector regression
GB	Gradient boosting	TBATS	Trigonometric box-cox trend seasonality
GBM	Gradient boosting machine	TS	Tabu search
GMDH	Group method of data handling	VAR	Vector autoregressive
GMM	Gaussian mixture model	VECM	Vector error correction model
GPM	Gray prediction model	VNS	Variable neighborhood search
GRU	Gated recurrent unit	XGBoost	Extreme gradient boost
LASSO	Least absolute shrinkage and selection operator	ADLM	Automated data logging and monitoring
LR	Linear regression	TLBO	Teaching–learning-based-optimization

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