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The growing role of artificial intelligence in smart container ports: its application and future research directions

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Abstract

Purpose – This paper aims to explore how artificial intelligence (AI) enhances container port operations, examining the interconnections between container ports and AI technologies and highlighting trends in AI applications for developing smart and green ports as well as future research directions.

Design/Methodology/Approach – This paper employs a literature review approach to analyze the role of AI in container port operations, focusing on the integration of various AI technologies and their implications for port efficiency and sustainability.

Findings – AI technologies, including 5G, machine learning, drones, big data, Industry 4.0 and blockchain, play a significant role in enhancing the operations of container ports. They contribute to improving port efficiency, enabling the development of smart ports and mitigating environmental impacts to foster green ports. The interconnections between these technologies and container ports present notable trends while also identifying avenues for future research.

Research limitations/implications – This paper is limited by the scope of the literature reviewed, which focuses primarily on technological applications rather than empirical case studies across diverse port contexts. Future research could explore comparative analyses of AI implementations in different port environments and assess long-term economic and environmental impacts.

Practical implications – Container terminal operators can leverage AI technologies to address inter-port and intra-port competition by boosting container throughput and port efficiency. Policymakers and port managers can utilize the trends in AI applications to guide the development of smart and green port strategies, investing in relevant infrastructure and technological frameworks.

Originality/Value – For enterprises and firms in maritime logistics, embracing AI in container port operations can lead to more efficient supply chain processes, reducing delays and costs.

Keywords Artificial intelligence, Machine learning, Container port operation, Smart port

Paper type Literature review

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1. Introduction

Container ports are essential facilities in global shipping networks, connecting the world and expanding the market opportunities for both national and international companies (Liu *et al.*, 2024; Zhou and Kim, 2020, 2021; Zeng *et al.*, 2024). With the ongoing development of economic globalization, container volumes continue to grow. Container terminal operators are competing with each other to attract more cargo to their container terminals by improving the quality of their services, enhancing the efficiency of port operations and reducing terminal handling charges, among other measures. Efficient container port operation and management will help increase container throughput and also promote the region's economic development (Cullinane and Wang, 2006).

With the increase in global container throughput, port authorities have begun constructing new container ports or expanding their existing ones. The Yangshan Deep-Water Port began trial operation at the end of 2017, and the Busan New Container Terminal was opened in 2010. Tovar and Wall (2019) found that large and complex ports will have higher productivity than smaller container ports. There are various methods to enhance the efficiency of container port operations and management. The efficiency of a container port is not only determined by its size; it is highly related to the advanced technologies integrated into the terminal operating system. After 1940, when the concept of artificial intelligence (AI) was first proposed, AI became a powerful tool for quality control, predicting failure modes, forecasting production markets and pricing. AI technologies, which are related to artificial neural networks, machine learning, fuzzy logic, deep learning, metaheuristic algorithms and hybrid techniques, have been widely adopted in various industries, including manufacturing, agriculture, education, finance, automotive and retail. New technologies could improve the performance of freight transportation systems (Crainic *et al.*, 2009). Recently, AI has been incorporated into national strategies by numerous governments, including China, the USA and the European Union. In 2017, the Chinese government released the "New Generation Artificial Intelligence Development Plan" for promoting the development of AI in China (Roberts *et al.*, 2020).

A tidal wave of innovation activities has swept the globe, promoting the maritime industry to embrace advanced technologies. The Maritime and Port Authority of Singapore and the Singapore Maritime Institute jointly organized the Next Generation Container Port (NGCP) Challenge in April 2012. The winner of the NGCP will get US$1 million grand prize. Additionally, many countries are planning to develop advanced container ports to achieve high throughput and increased productivity in land and labor. China developed the world's largest automated cargo wharf, Shanghai Yangshan Port (Luo, 2019). Singapore has been developing the Tuas mega port by using state-of-the-art technology to make it more automated, intelligent and sustainable. Scholars have also started to focus on AI technologies that can be adopted in the maritime industry. Munim *et al.* (2020) conducted a bibliometric analysis of AI in the maritime industry. Wilson (1997) applied AI techniques to determine the cargo stowage for a deep-sea container ship. Salido *et al.* (2009) developed a planning tool by using AI for the container stacking problem.

Countries such as China, the United Kingdom (UK), the United States and Singapore are competing for the future market in the maritime sector. Many countries and organizations have issued different policies related to the future maritime industry, such as the Maritime 2050 of the UK. Many countries want to expand their maritime power by embracing AI technologies. The Chinese central government aims to construct several intelligent and green ports by 2050 to revive the national economy and promote intelligent shipping services, safety, environmental protection and efficiency. Scholars have been applying AI technologies for developing smart ports, such as the Q-learning technique for automated guided vehicle (AGV) systems (Jeon *et al.*, 2011; Lim *et al.*, 2003). Jun *et al.* (2018) studied the impact of smart ports on the Korean national economy and found that smart port has a positive influence on the national economy. Many countries, scholars and international organizations are convinced that AI will bring profound changes in future port construction.

Smart port (intelligent port) is a new, emerging and evolving concept that has been proposed in recent years. There is no precise definition of a smart port. Many countries and private companies have launched smart port-related projects. Smart Port Amsterdam was proposed by the Port of Amsterdam to achieve a faster, cleaner and leaner port by utilizing sensory data [1]. The smart port was developed by the Port of Hamburg with state-of-the-art digital intelligence. The Port of Hamburg has developed an intelligent port management system, which enables smooth and efficient operation. The Port of Singapore and the Port of Rotterdam are also launching a smart port project to accelerate innovation. The Korean government launched a state project to establish a smart logistics port in Busan. China has developed the world's first fully 5G-connected smart port. Four companies, including Huawei, Zhenhua Heavy Industries Company (ZPMC), China Mobile and Vodafone, drafted a smart port white paper.

Remaining globally competitive as a container port is the main priority for a country or company in developing a smart port. Another important issue is protecting the environment when developing a smart container port. Container ports generate pollution that damages the natural environment. Specifically, air and oil pollution stem from the operation of container vessels, terminal trucks, yard gantry cranes, and quay cranes. Additionally, container ports will also generate excessive noise, pose health risks and present ecological threats. Several factors, including lower carbon emissions and reduced air pollution, contribute to evaluating the environmental friendliness of a smart port. A smart port has two primary objectives: maintaining global competitiveness and preserving the environment. An AI-enabled port ecosystem, powered by port community systems, could enhance collaboration among various parties, including port authorities, cargo owners and third-party logistics providers, as it aligns their individual digital roadmaps.

This paper focuses on the AI technologies used in the development of a container port. The contributions of this paper are summarized as follows. (1) This paper introduces a new perspective for providing a systemic review of the development of container ports and AI. (2) This paper presents the AI-related technologies, which has been used in container port operation and management, and also summarizes the new technologies that can be adopted for the development of the smart port of the future. (3) The findings of the paper give significant new insights, which help the academic and industry. (4) This paper outlines the scope of the topic of AI used in the development of container ports.

The remainder of this paper is organized as follows. Section 2 introduces the history of AI, the shipping industry and the container port. Section 3 presents the AI technology adopted in the container port. Section 4 presents applications of AI for container ports. Section 5 discusses the advanced technologies that could be adopted in container ports as well as future research topics. Finally, the conclusions and discussions are presented in Section 6.

2. AI and container port

2.1 A brief history of AI

The birth of AI is often attributed to the Dartmouth conference of 1956, widely considered the founding event of AI. AI is one of the most elusive subjects in computer science. In 1956, John McCarthy coined the term "artificial intelligence" at the Dartmouth conference, marking the first academic conference dedicated to the subject.

Between 1956 and 1974, AI experienced its golden years, during which many essential native algorithms were proposed. The development of AI has not always been smooth. AI encountered its first AI winter from 1974 to 1980. Fortunately, this AI winter is not so long. After 1986, when back-propagation was proposed, AI embraced another boom. However, this period lasted only seven years (from 1980 to 1987). Between 1987 and 1993 was another long winter for AI. After IBM's Deep Blue defeated a chess grandmaster, AI was growing very fast. Figure 1 shows the AI winter and the related development of algorithms.

In the early stage of AI, native algorithms were proposed. After that, machine learning dominated the AI area for a long period from 1960 to 2010. The rise of the graphics processing unit and the exponential growth of available data have promoted the boom of deep learning and deep reinforcement learning.

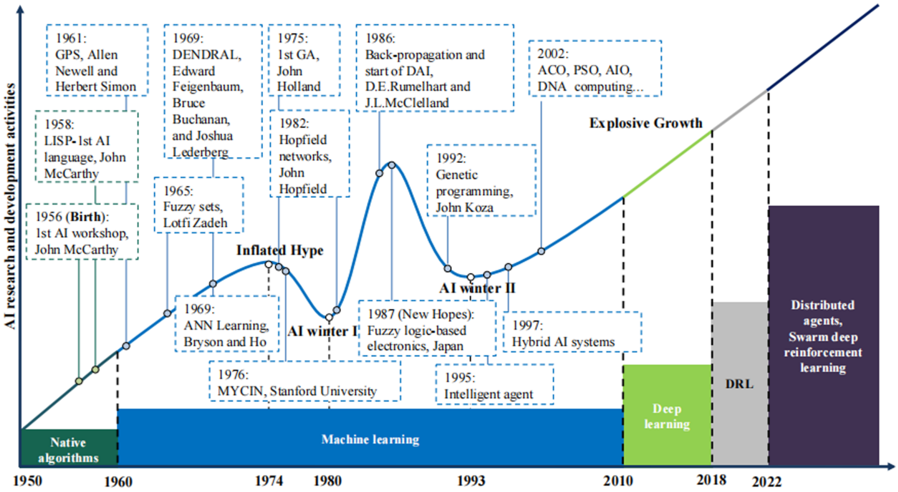


Figure 1. AI winters and the evolution of corresponding optimization algorithms

In 2016, AlphaGo defeated the legendary Go player Lee Sedol from South Korea. More than 200 million people watched this competition, and the general public began to experience the power of AI. Nowadays, AI is everywhere and has been integrated into humans' daily life, such as AI-driven vehicles, AI factories, AI cities and AI schools.

In recent years, many countries and international organizations have proposed AI-related policies to promote the development of the AI industry and accelerate intelligent transformation. In 2018, the European Association for Artificial Intelligence launched a workshop to explore the possibility of cooperation among European countries. The European Union launched the Horizon 2020 plan to promote the development of AI in European countries. In 2017, China released a plan named "New Generation Artificial Intelligence Development Plan" to improve its international competitiveness and promote its economic growth simultaneously.

2.2 A brief history of container port development

A container port is a node in maritime supply chains, providing a facility where cargoes are loaded, unloaded and transshipped between different modes of transportation, such as vehicles, vessels or trains.

Before using the container for loading and unloading cargoes, the process is difficult, causing many delays and resulting in lost or stolen items. Suppose the containers are delivered by truck trailers and directly loaded onto the vessel, rather than being transferred to different containers. In that case, it will save time and cost for both the vessel carrier and the truck carrier. At the early stage of the shipping container, companies start to containerize cargoes. But different companies adopted different sizes of containers, which makes the loading and unloading of ships very labor-intensive and time-consuming. Malcolm McLean, a transport entrepreneur who is the father of containerization, attempted to design strand containerized containers in the early 1950s. In 1968, the International Standardization Organization released the industry standard for referencing cargo volumes, including 20-foot and 40-foot shipping containers. Standardization of the container makes the operation of the container at the container port more efficient. Containerization sped up the boom of the maritime industry.

Elizabeth Marine Terminal, which was opened by the Port of New York and New Jersey in 1962, is considered to be the world's first container port. Container port development is closely tied to several key aspects, including technology and capital. Container port development is highly capital-intensive, requiring a substantial amount of financing for port investment. At the early stage, container ports are owned by the port authority. Container port privatization is gaining popularity as a means for ports to gain a competitive advantage by granting concession contracts to container terminal operators. The privatization of container ports accelerates container development because private companies are more efficient than public ports, and more social capital is being invested in container ports.

Container ports can be classified into various categories based on different criteria, including land ownership, business model, cargo weight, influence area, geographical location, tax policy zone and traffic type. According to the business model, a port can be divided into a public port, a tool port, a landlord port and a private port. Based on the port's influence area, a port can be considered a local port, regional port, national port, continental port or global port.

Port development can be classified into different stages according to various criteria, such as port functions, dominant cargo flows or technologies. Different researchers or organizations classified the port developments into different generations. There are three popular definitions. Molavi *et al*. (2020) and UNCTAD classed port development into five generations, as shown in Figures 2a and 2b, respectively. Heilig *et al*. (2019) summarized the digital transformation of maritime ports into three stages: first generation (paperless procedures prior to the 1980s), second generation (automated procedures between the 1980s and 2000s) and third generation (smart procedures after the 2010s).

Due to the time and capital costs, vessel carriers are highly sensitive to the time spent in port. Vessel carriers prefer container ports that have a shorter time in port, which is generally indicative of high port efficiency and trade competitiveness. The study by UNCTAD (2019) shows that larger vessel sizes will spend less time in port. The vessel's capacity is increasing steadily. The capacity of the largest ultra-large container ship exceeds 20,000 twenty-foot equivalent units (TEU). The development of container ships drives the development of container ports.

We collected the annual statistical data provided by the Port of Hong Kong [2]. From these data, we found that the average time in port for dry bulk carriers and conventional cargo vessels significantly reduced after 2005. Kwai Tsing Container Terminal No. 9, the largest container terminal at Kwai Tsing Container Terminal, was completed in 2005.

Recently, an increasing number of countries have focused on developing advanced container ports. China developed the Shanghai Yangshan Deep-Water Terminal, the largest fully automated container terminal, and Shanghai Port ranks as the world's first container terminal in terms of container throughput (Luo, 2019). Daewoo Shipbuilding & Marine Engineering collaborated with the Dutch Port of Rotterdam Authority to develop the interface between a smart ship and a smart port, aiming to achieve maritime digitalization (Hakirevic, 2020).

To maintain its competitiveness, the container port plans to develop its next-generation container ports. Kim *et al*. (2012) reviewed various new conceptual handling systems in container terminals. Recently, Gharehgozli *et al*. (2019) summarized the future design of container terminal layouts. Zaerpour *et al*. (2019) proposed a vertical expansion as a new solution for future container terminals to increase their capacity. Figure 3 shows an example of vertical expansion of a container port. High-bay storage systems proposed by BOX BAY FZCO are a new type of container storage system, similar to materials' handling systems in a warehouse for general cargo. Figure 4 illustrates an example of a high-bay storage system in a container port.

Eaglerail Container Logistics and Shanghai ZPMC designed the world's first automated, 100% electric, overhead container transportation solution, which can improve the efficiency of port and inter-modal operations. The advanced container port usually refers to a smart container port. Environmental issues have received increasing attention from the public sector. Most of the container ports are private, commercial businesses that are sensitive to capital investment unless absolutely necessary. Hence, it requires government-made environmental

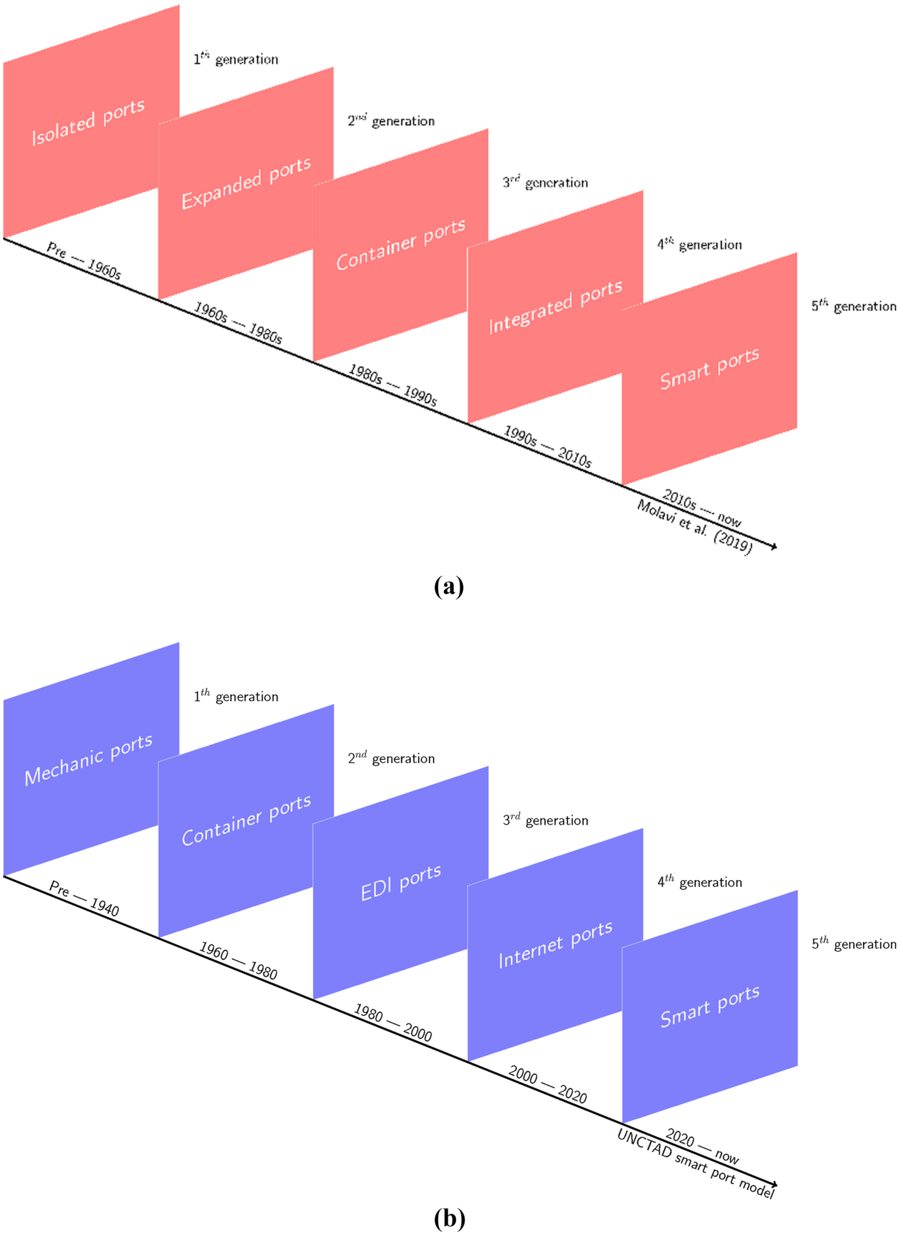


Figure 2. Two models of port development: (a) five generation models proposed by Molavi *et al.* (2020) and (b) UNCTAD smart port model

regulations to incentivize the maritime industry to reduce emissions. Recently, many countries released policies for developing green ports. Government and international nonprofit organizations encourage industries to collaborate in protecting the environment, such as reducing vessel and port emissions by utilizing electrical equipment.

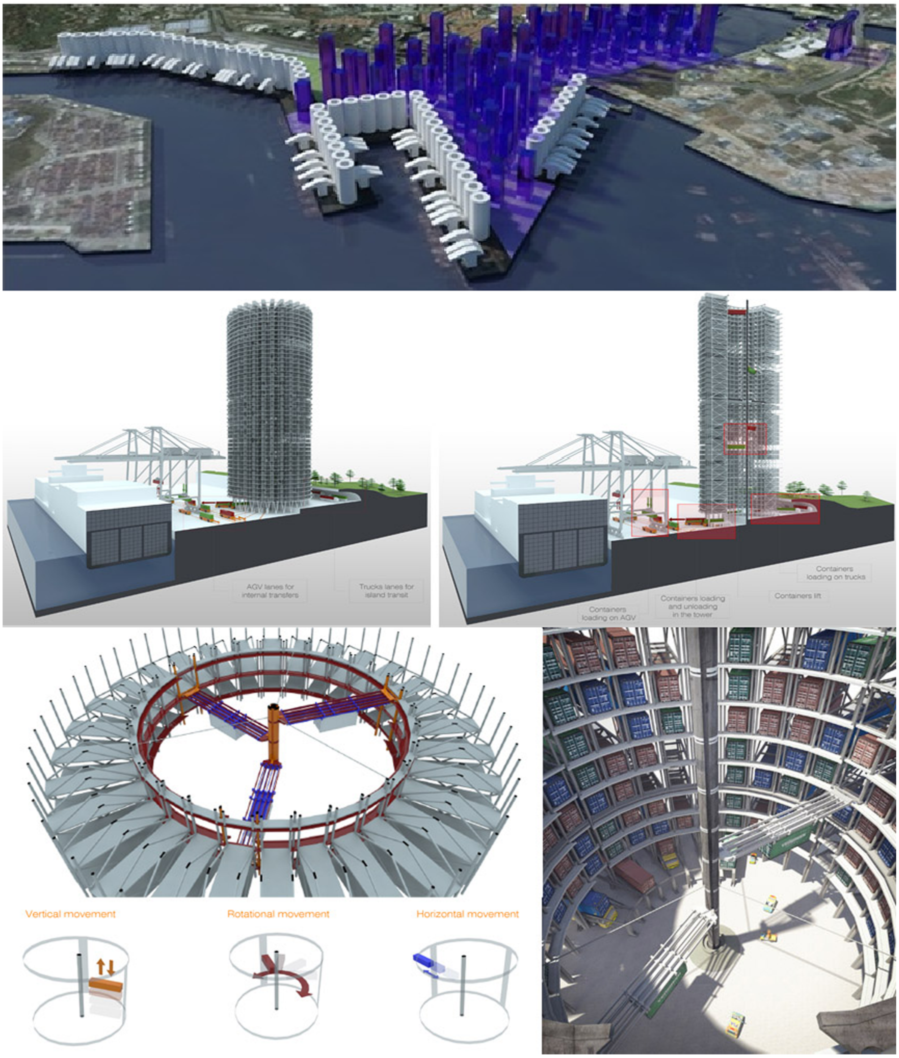


Figure 3. An example of vertical expansion [3]

2.3 Policies (activities) for smart port in the selected countries

To promote national competitiveness in the maritime industry, various policies and activities have been launched by different countries, including the UK, Singapore, the Republic of Korea, China and Germany. In this subsection, the policies and activities related to the container port are presented.

2.3.1 Singapore. The Port of Singapore is a crucial port for transshipping containers and connecting to many international hub ports. The Port of Singapore plays a crucial role in Singapore's national economy.

The development of Singapore is highly dependent on international trade. First, the Singapore government launched a free and open multilateral trading system to attract international trade. Now, the maritime industry is a critical pillar supporting Singapore's

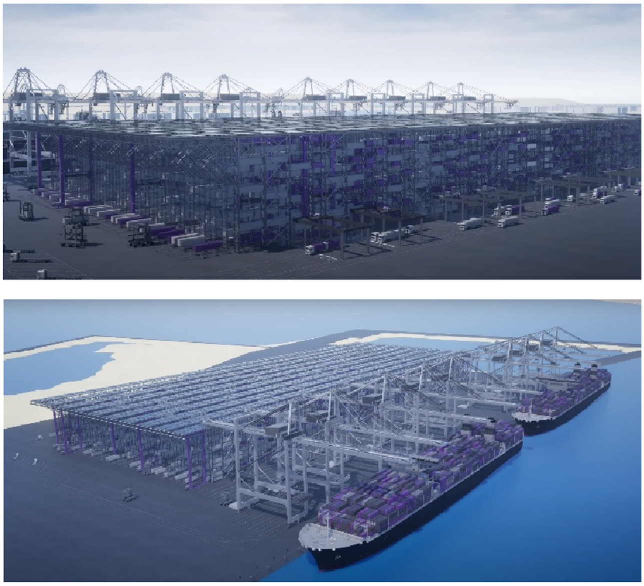


Figure 4. An example of a high bay storage system container port [4]

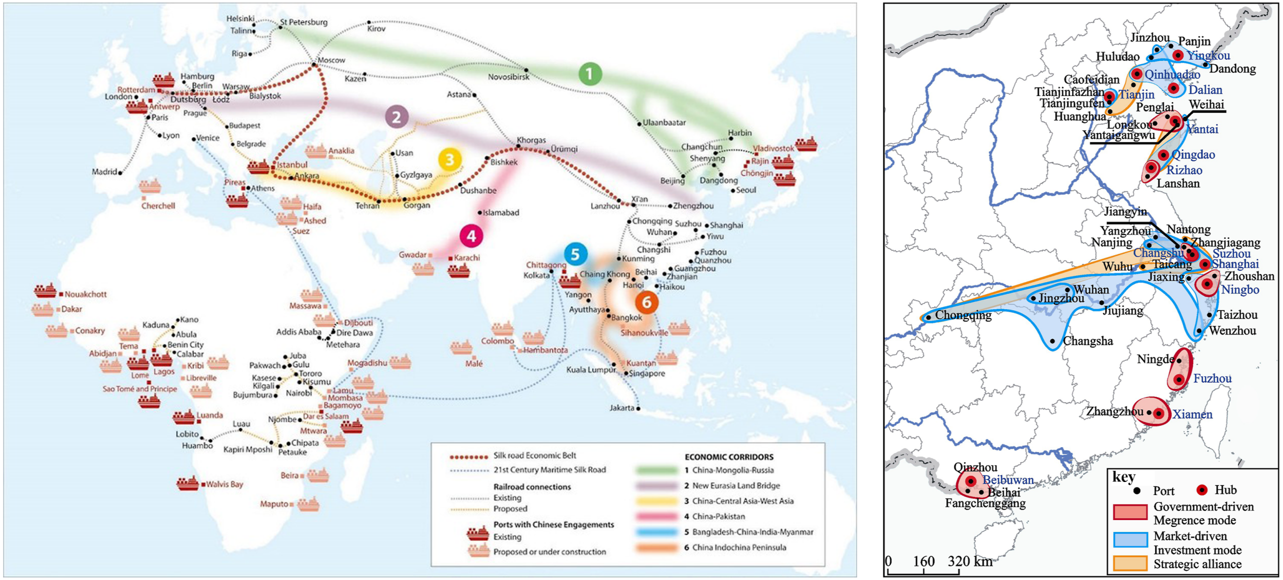
national economy. In 2015, the maritime sector contributed about 7% to Singapore's GDP. The Prime Minister of Singapore stated, "Rethink the future of shipping".

The Singapore government proposed port-city policies and believes that automation could boost the efficiency of the container port. The aim of Singapore is to build an intelligent and sustainable port. To achieve this goal, many activities related to designing the next-generation container port have been done. In April 2012, two Singaporean organizations, including the Singapore Maritime Institute and the Maritime and Port Authority of Singapore, designed the NGCP challenge to encourage industry and academia to design a high-throughput and high land and labor productivity container port. The winner of NGCP will receive the $1 million grand prize [5]. The Singapore government plans to close all the current container terminals by 2027 and is constructing the new Tuas Mega Port. The Tuas Mega Port, with a capacity of 36 million TEUs, will be the world's largest fully automated container port, scheduled for completion in the 2040s.

2.3.2 China. Among the Top 10 busiest container ports, seven are owned and operated by China. As the world's leading exporter, China has a significant influence on international commercial trade in the maritime sector.

The Chinese government has developed a three-step plan to promote innovation in the maritime industry. Step 1: Become a global innovation hub by 2025. Step 2: Own the core intelligent shipping technology by 2035. Step 3: Develop a high-quality intelligent shipping system by 2050. The Chinese government also introduced two additional policies: port integration strategies and the Belt and Road Initiative (BRI), as illustrated in Figures 5a and 5b, respectively.

The "one port-one city" pattern does not fit China, given its economic retardation (Wu and Yang, 2018). The Chinese government has found that many ports are experiencing an oversupply of port resources. In 2003, the Ministry of Transport of China appealed for port integration strategies to promote cooperation among ports. There are three types of integrations: (1) port integration across neighboring regions, (2) jurisdictional port integration and (3) port internal integration.



(a)

(b)

Figure 5. BRI and port integration: (a) one (land) belt one (maritime) road (OECD, 2018) and (b) port integration in China (Wang *et al.*, 2015)

BRI is a global infrastructure development strategy that was proposed by the Chinese government in 2013. BRI aims to boost the international trade network along the “21st Century Maritime Silk Road”.

2.3.3 The Republic of Korea. The Republic of Korea has the world’s fifth-busiest container port, and the Korean government has been establishing a smart port system by proposing various policies.

An important policy is the National Logistics Master Plan (2011–2020), which was proposed in 2011. To raise Korea’s competitiveness in container ports and foster the maritime industry to superpower levels, the Korean government also established a port development policy in 2012.

To facilitate suitable development, the Korean Ministry of Maritime Affairs and Fisheries launched an air quality control program in 2020. According to the air quality control program, South Korean ports and coastal areas are selected as emission control areas. The Korean Ministry established a smart maritime logistics promotion team to enhance the application of AI technologies in the maritime sector.

In July 2020, the Korean government announced the New Deal programs, which provide a blueprint for South Korea’s next hundred years of development. Digital New Deal and Green New Deal are two main issues of the New Deal. In response to the New Deal programs, the Incheon Port Authority launched a comprehensive automated system plan.

2.3.4 The United Kingdom. The English Channel is crucial for the UK because it serves as a vital shipping route for international trade. The UK government’s vision and ambitions for the future of the British maritime sector are to become the heart of a global maritime autonomy industry. The UK government has developed a plan called Maritime 2050: Navigating the Future.

In the Maritime 2050 plan, the UK government encourages innovation and the adoption of advanced technologies in container ports to develop smart ports.

2.3.5 Germany. Germany launched an energy transition and cleaner air in Hamburg to reduce carbon emissions. The Port of Hamburg plans to replace diesel with lithium-ion batteries for its AGVs.

Container ports are a significant source of environmental pollution in coastal urban areas. Reducing carbon emissions in ports is essential for the sustainable development of container ports. Many countries and organizations, including the Organization for Economic Co-operation and Development, Oslo and Paris Conventions, the African Development Bank, the International Convention for the Prevention of Pollution, International Maritime Organization, European Sea Ports Organisation, Central Dredging Association, appeal for developing the ecosystem-based port (Chen *et al.*, 2019). Different countries and organizations may propose varying policies or regulations for ecosystem-based ports, as listed in Table 1.

OECD, Organization for Economic Co-operation and Development; OSPAR, Oslo and Paris Conventions; ADB, the African Development Bank; MARPOL, the International Convention for the Prevention of Pollution; IMO, International Maritime Organization; ESPO, European Sea Ports Organisation; CEDA, Central Dredging Association

2.4 Current methods in container ports

To analyze the evolution of previous studies related to container ports, this section examines the popular methods, influential authors and their affiliations. This paper adopted the Aminer [6] as an analysis tool, which provides a comprehensive search and mining service.

To investigate the technology foresight of container ports, we used the trend function provided by Aminer, considering 2000 as the base year. The technology foresight of the container port is shown in Figure 6. From 6, we found that data mining, genetic algorithms, neural networks, algorithm design and analysis, information technology, computational modeling and geographic information systems are the main methods used in container ports.

Table 1. Policies and regulations related to ecosystem-based ports

Policies or regulations	Countries or organization
Inclusive green economy	United Nations
Concept of green growth	World Bank
Green growth port-cities	OECD
Sustainable use of the seas	OSPAR
Green economy	ADB
Prevention of pollution from ships	MARPOL
Reduce greenhouse gas emissions	IMO
MarCom green port	PIANC
EcoPorts	ESPO
Sustainable dredging	CEDA
Clean maritime plan	UK
Green port	China

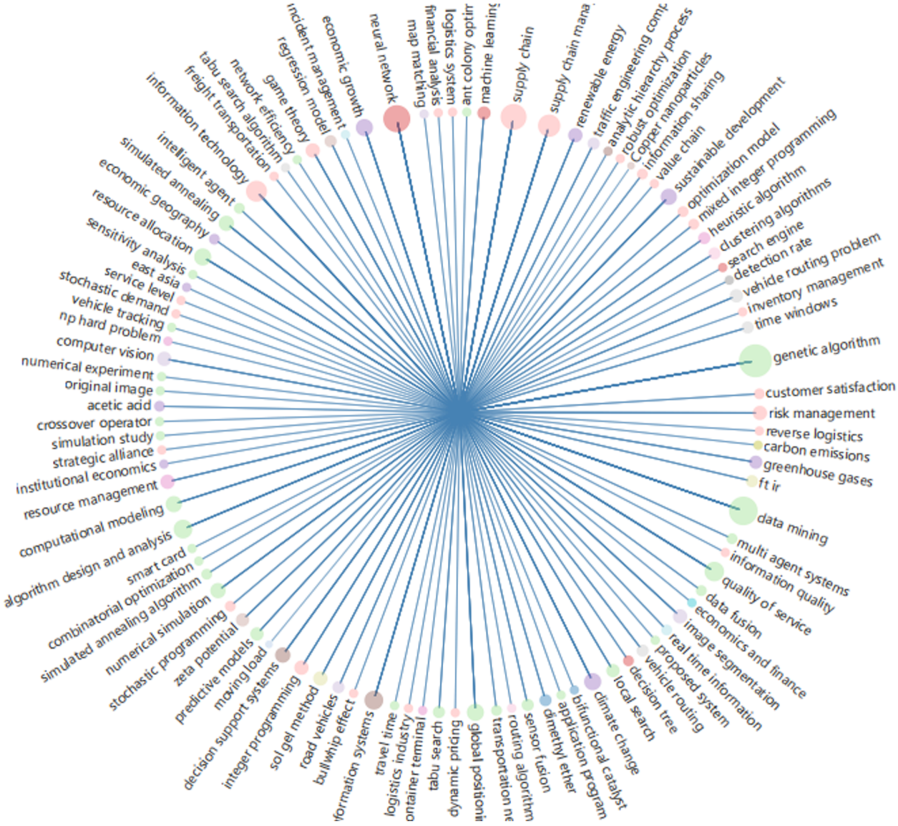


Figure 6. Technology foresight of the container port

Figure 7 shows the top 10 technology foresight in container ports according to the research leadership index. Among these Top 10 technology foresight, machine learning, which is directly related to AI, ranks in the second position. Increasingly, scholars are focusing on the application of machine learning in container ports, and this trend has gained momentum since 2016.

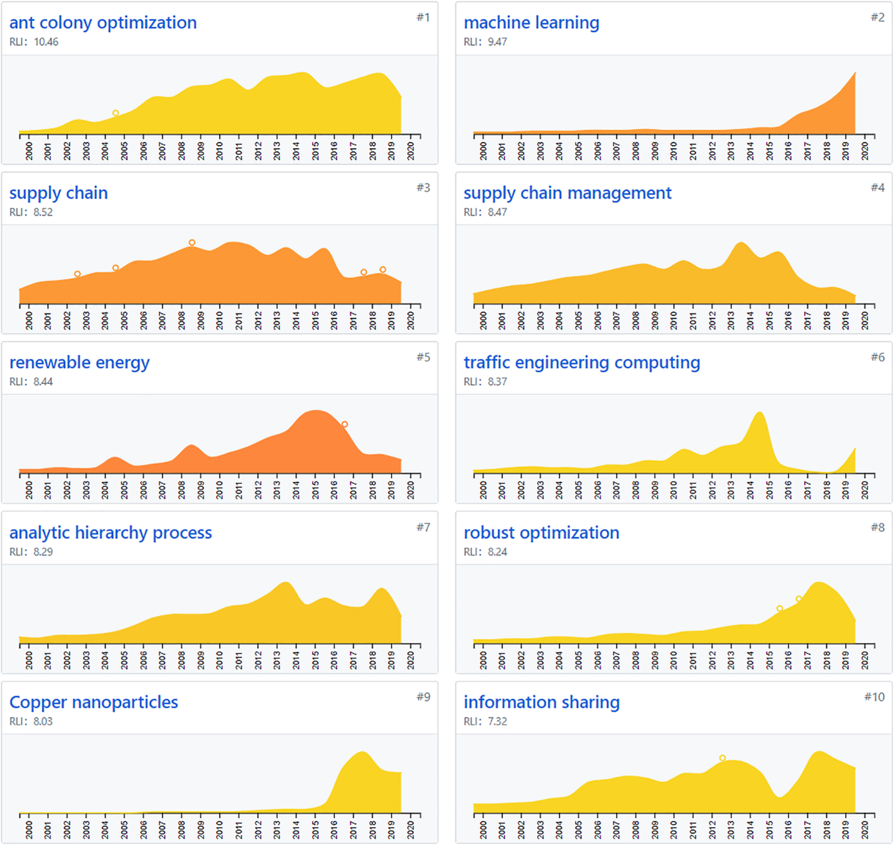


Figure 7. Top 10 technology foresight in container port according to the research leadership index

3. AI technologies used in container ports

A container port is a highly complex system that consists of numerous subsystems, including the straddle carrier system, the yard management system, the quay crane system, the AVG scheduling system and the gate appointment system, among others. Container ports are becoming larger and larger with the evaluation of container vessels. In recent years, many container ports have been upgrading their operations to automate container handling using modern technologies.

AI is a powerful tool and can be adept at solving complex systems. AI technology encompasses a wide range of computer science technologies, including high-performance computing, artificial neural networks, machine learning, reinforcement learning, deep learning, metaheuristics and optimization. Figure 8 gives an overview from top to bottom of AI. The application of AI in container ports depends on the availability of hardware and software facilities as well as national AI policies. This section introduces the AI technology used in container ports.

3.1 High-performance computing

High-performance computing, which executes tasks in parallel by clustering computers, is a linchpin in machine learning and deep learning for training models. Many of the scheduling

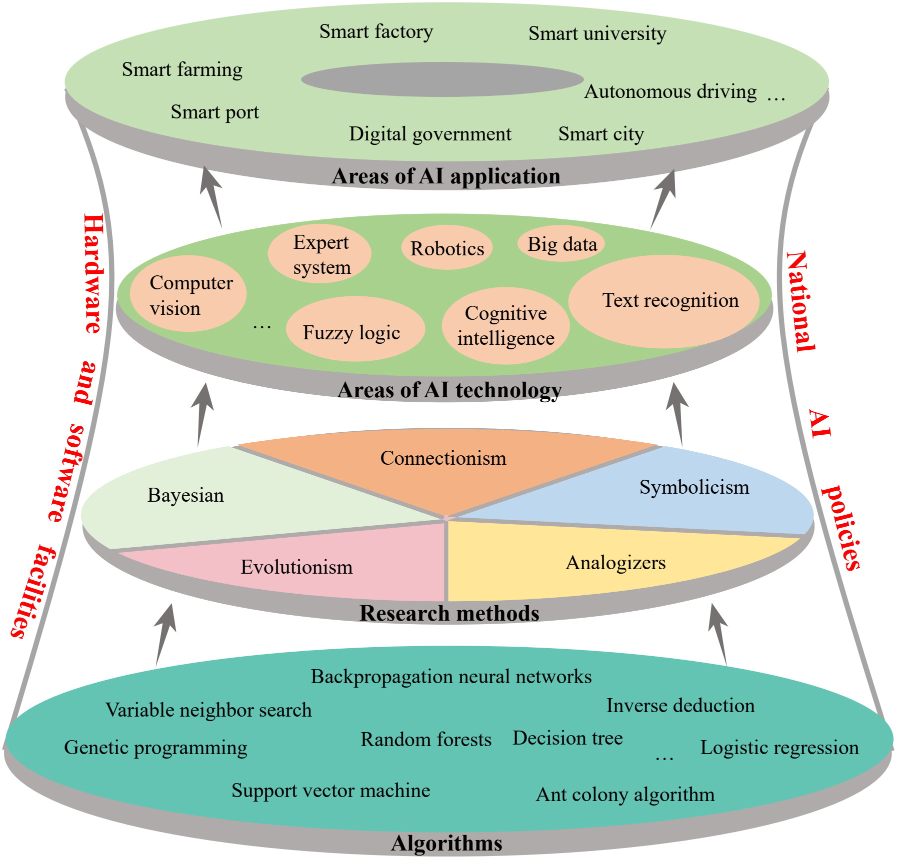


Figure 8. From top to bottom of AI

problems in container ports, such as the berth scheduling problem and the crane scheduling problem, are NP-hard or NP-complete problems. As the scale of these scheduling problems increases, it becomes increasingly time-consuming to obtain the optimal solution using exact algorithms, including branch-and-cut, branch-and-bound and branch-and-price. Many scheduling problems in container ports typically require real-time responses. Hence, the scheduling algorithms that were adopted to solve real-time scheduling problems, including twin stacking cranes, multiple yard cranes, truck scheduling and twin rail-mounted gantries, should return an acceptable solution quickly.

Designing an efficient algorithm is one method to reduce the computational time of scheduling algorithms. High-performance computing is a critical technique for accelerating the computing process by executing multiple tasks concurrently and efficiently and has been successfully used in environmental modeling and biochemistry, especially for large-scale scheduling problems. Researchers in the maritime sector started to develop parallel models (Li and Shen, 2015). Ghiani *et al.* (2003) emphasized and designed parallel computing strategies for real-time vehicle routing. Developing new terminal operating systems that are integrated with high-performance computing is a growing trend. Figure 9 illustrates a smart terminal operating system with high-performance computing capabilities.

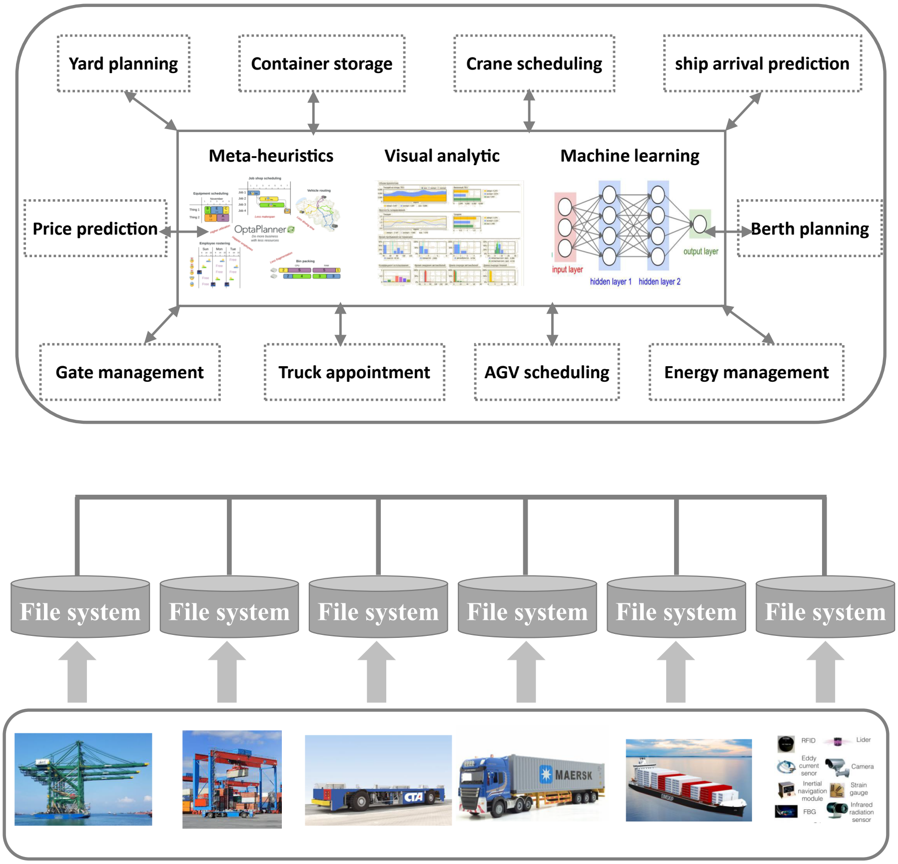


Figure 9. A smart port operating system with high-performance computing

3.2 Artificial neural network

Artificial neural networks (ANNs) are often referred to as neural networks, which mimic the working mechanism of biological neural networks. There are various types of ANNs, including deep belief networks, recurrent neural networks, modular neural networks, deep neural networks and convolutional neural networks.

The ANN has a powerful approximation ability, which can be utilized to solve complex systems for both industrial and academic communities. The applications of ANN vary from pattern recognition to network modeling. The early applications are in computer science areas, and ANN can also be used to estimate port planning parameters by analyzing and learning from historical data to inform the port planning process (Garcia *et al.*, 2014). Gao *et al.* (2018) used a recurrent neural network to forecast daily container volume. Neural networks have been employed in container ports for a considerable time to forecast container flow (Milenkovic *et al.*, 2019; Tsai and Huang, 2017; Huang, 2018).

Forecasting is a fundamental area for deep learning and machine learning, which has been widely applied in climate modeling, finance, the shipping industry, bitcoin pricing, solar radiation and medicine. Deep learning and machine learning are particularly well suited for forecasting time-series data. The container port generates a considerable amount of data, including daily container volumes, vessel arrival information, container arrival information, sensor-collected images and records of yard and quay crane movements.

Container throughput forecasting is a significant topic in the maritime industry and has been extensively studied using traditional forecasting methods, such as the gray model, seasonal autoregressive integrated moving-average, trigonometric regression model and wavelet transforms (Xie *et al.*, 2019). Over the past decade, machine learning has been increasingly adopted in container throughput forecasting (Xiao *et al.*, 2014; Huang, 2018; Tsai and Huang, 2017).

In recent years, forecasting with machine learning or deep learning methods has also been used in other applications, including ship arrival prediction (Yu *et al.*, 2018), prediction of container damage (Petriu, 2018), price prediction (Ubaid *et al.*, 2020), forecasting late arrivals (Pani *et al.*, 2014), fuel consumption estimation (Le *et al.*, 2020) and dynamic pricing (Ding *et al.*, 2021). The application of machine learning and deep learning methods in container ports for forecasting is growing rapidly.

3.3 Metaheuristics

Metaheuristics are modern optimization methods that have been widely used in industries. Meta-heuristics can be classified into different categories based on classification criteria: nature-inspired and non-nature-inspired; population-based search and single-solution-based search; deterministic and stochastic; iterative and greedy; parallel and non-parallel. To solve complex problems, hybrid meta-heuristics are usually designed, such as combining tabu search and simulated annealing. Combining machine learning and metaheuristics will improve efficiency and effectiveness compared to using either machine learning or metaheuristics alone. Metaheuristics, including genetic algorithms, variable neighborhood search, greedy randomized adaptive search procedure, simulated annealing, tabu search, scatter search, evolutionary programming, particle swarm optimization, ant colony optimization, differential evolution and estimation of distribution algorithm, have been widely used in container terminal operations and management.

Figure 10 illustrates the total number of publications related to container ports and metaheuristics published each year [7]. From Figure 10, we can see that the number of papers adopting metaheuristics has increased, especially over the past decade.

Figure 11 is a horizontal bar chart that displays the number of literature associated with different affiliated institutions. From Figure 11, we can see that Universität Hamburg has the highest number of publications, approaching 20. In contrast, Shanghai Jiao Tong University has the lowest number among the listed institutions. The other institutions fall at various points in between, showing a clear variation in the amount of literature produced by each affiliated

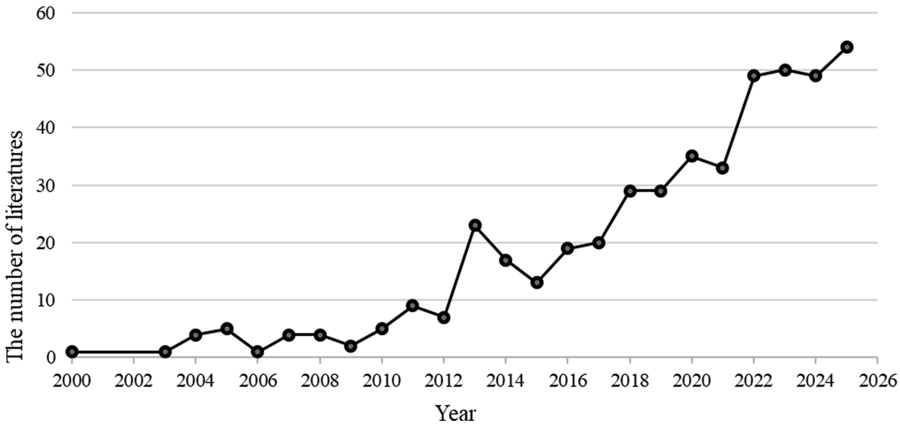


Figure 10. Number of publications in container ports with metaheuristics

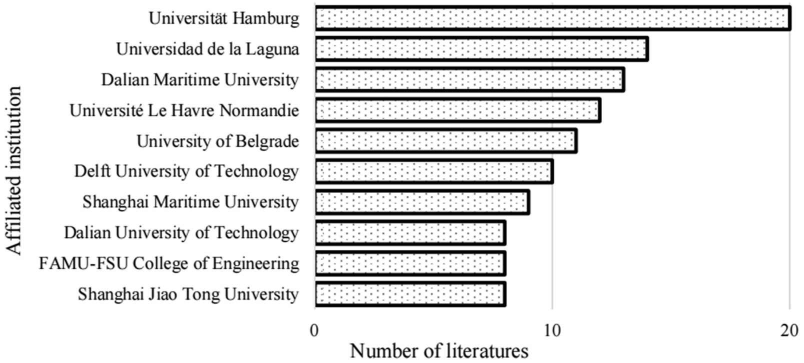


Figure 11. Number of publications classified by affiliated institution

institution. This chart effectively visualizes the comparative output of literature across various academic and research institutions.

Figure 12 is a horizontal bar chart illustrating the number of literature by different countries/regions. It is evident that China has the highest number of literature paper, nearly reaching 100. The United States has a significantly lower number, around 30, and the remaining countries/regions (France, Germany, the UK, Spain, Canada, Italy, Morocco and the Netherlands) have relatively similar and lower counts, all below 30.

Figure 13 displays the number of literature associated with different financial sponsors. From Figure 13, it can be seen that the National Natural Science Foundation of China has the highest number of publications, approaching 45. In contrast, Fundação para a Ciência e a Tecnologia has the lowest number among the listed sponsors. The other sponsors fall at various points in between, showing a clear variation in the amount of literature supported by each financial sponsor.

3.4 Machine learning

Machine learning is a subset of AI that has a wide range of applications, particularly in solving industrial problems. The main steps of machine learning consisted of five steps: (1) identify the

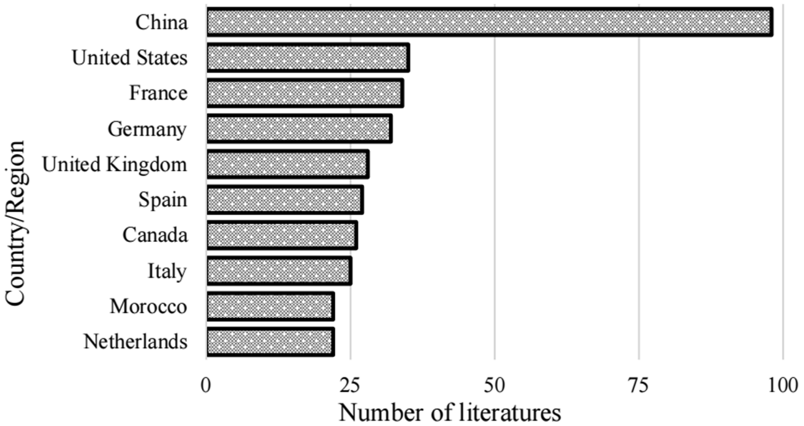


Figure 12. Number of publications by country/region

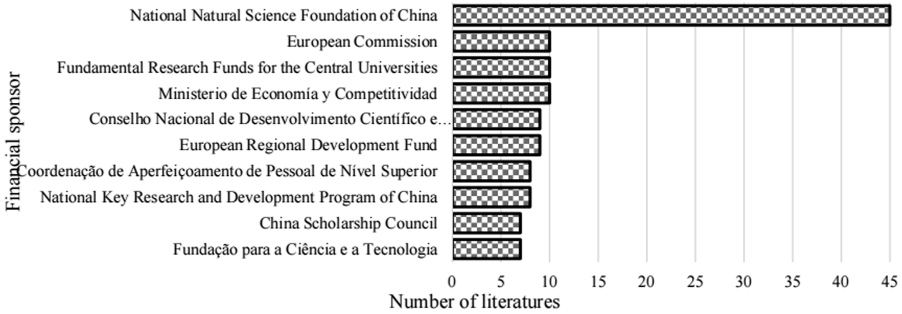


Figure 13. Number of publications in container ports with financial sponsors

problem, (2) data preparation and cleansing, (3) model exploration, (4) model refinement and (5) model training.

Many container ports are embracing machine learning to improve their productivity. The Port of Rotterdam is developing a smart port by utilizing Awake.AI (https://www.awake.ai), a company that provides smart solutions for maritime logistics by leveraging the latest advancements and digital innovations in modern cloud platforms.

Scholars also investigated how to design machine learning for container port operation and management. Xie and Huynh (2010) adopted machine learning to predict daily truck volume at a seaport terminal. de León *et al.* (2017) proposed a machine learning–based system for berth scheduling at bulk terminals. Kim *et al.* (2000) introduced a classification procedure for inductive learning to determine the storage location of an arriving export container. Pani (2014) employed machine learning to manage a container terminal, considering the uncertainty of vessel arrivals. Recently, Zhang *et al.* (2020) proposed a machine learning-driven method to solve the container relocation problem. Millefiori *et al.* (2016) developed a distributed machine learning approach to estimate seaport operational regions using a large amount of vessel data. Many problems, such as berth allocation problems, in container ports, belong to combinatorial optimization. Scholars have recently found that machine learning can be adopted to solve combinatorial optimization problems (Bengio *et al.*, 2020).

3.4.1 Reinforcement learning. Reinforcement learning is a branch of machine learning that has been applied to real-time decision-making, robot navigation, learning tasks, skill acquisition and game AI (Jin *et al.*, 2024; Chen *et al.*, 2024a). One popular method of reinforcement learning, which has been used in container port operation and management for a long time, is Q-learning.

The early application of reinforcement learning in container ports is exemplified by Q-learning, which was used by Lim *et al.* (2003) to design guide-path networks for the AGV system. Later, Hirashima *et al.* (2006) successfully used Q-learning for container marshalling. After that, Zeng and Yang (2009) applied Q-learning to scheduling yard cranes and yard trailers. Fotuhi *et al.* (2013) employed Q-learning to solve the yard crane scheduling problem, analyzing the turn time of container trucks. Recently, Ma *et al.* (2020b) developed a deep reinforcement learning method to detect collision avoidance under COLREGS for unmanned surface vehicles. Luo and Huang (2018) used reinforcement learning for empty container repositioning.

3.4.2 Deep learning. Deep learning is a subset of machine learning that utilizes more complex neural networks than those used in traditional machine learning and is capable of unraveling enormous amounts of unstructured data. Deep learning is used to solve more complex problems when the input data set is diverse, unstructured and interconnected.

The container terminal operating system is a complex system, with its subsystems interconnected; yet, each subsystem handles a distinct type of data. Hamburg Port Consulting

(HPC) is developing a deep learning solution for container dwell time prediction, utilizing deep learning methods to identify hidden patterns in two years of historical data on container movements. HPC tries to integrate the proposed deep learning solution into the existing terminal operating system, and from its analysis, it finds that the deep learning solution can reduce costs and greenhouse gas emissions. Kamal *et al.* (2020) proposed a pixelization method to predict the completion time of the event log of the container-handling process in the container port. Metzger *et al.* (2019) proposed a data-driven deep learning approach for proactive terminal process management.

3.5 Data-driven optimization

Optimization models in container ports are positively related to the input parameters of the models themselves (Chen *et al.*, 2024b). The input parameters are usually uncertain. Two traditional methods, including stochastic and robust optimization methods, have been widely adopted in container port optimization for models that know the density or exact distribution of the models' input parameters. The robustness is too conservative, and it is not easy to obtain the exact distribution of the models' parameters for the modern container ports. With the evolution of container ports, an increasing number of sensors are being integrated into current automated container ports, enabling the collection of a large amount of data. Container ports accumulate vast amounts of empirical data, which can be used to investigate the properties of optimization models using machine learning or other methods.

Distributionally, robust optimization, a data-driven optimization method, has attracted many researchers from both academia and industry in operations research and statistical learning communities. Distributionally, robust optimization is an intermediate optimization method between stochastic and robust optimization.

The early data-driven approach was adopted in simulation for yard crane dispatching by Guo *et al.* (2008). Recently, researchers in the maritime industry have begun to utilize data-driven optimization in container port operations and management. Tsang and Mak (2015) used distributionally robust optimization for empty container repositioning. Metzger *et al.* (2019) developed a data-driven deep learning model for proactive terminal process management by using big data. Heilig *et al.* (2019) summarized data-driven decision-making in container port operation and management. Zhang *et al.* (2020) proposed machine learning-driven algorithms for the container relocation problem, and the proposed method could find a tighter lower bound. Chen *et al.* (2020) adopted data-driven genetic programming for container truck dispatching. Figure 14 shows an overview of data-driven optimization in a container port.

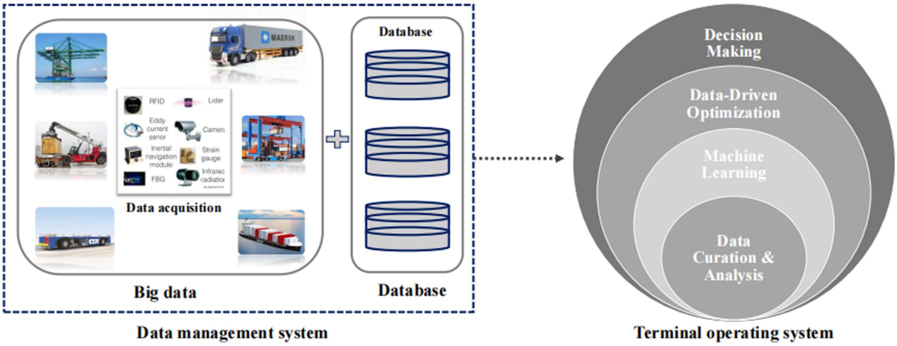


Figure 14. An overview of data-driven optimization in a container port

3.6 Review of AI technologies in container ports

This subsection examines the trends in published papers utilizing AI technologies in container ports and categorizes these papers by domain. Before 2006, there were few studies that utilized AI technologies to address container port-related problems, and it was a relatively dormant phase. Between 2006 and 2018, an increasing number of papers were published using AI technologies in container ports, marking a wave phase. From Figure 15, we can see that the total number of papers related to container ports began to experience exponential growth after 2019. Due to incomplete information, we omit the papers published in 2021. From Figure 15, we observe that the container port area will increasingly apply AI technologies.

Figure 16 shows the literature by country/region related to AI. From Figure 16, we can find that China has the highest number of literature paper, nearly reaching 27. India has a significantly lower number, around 18, and the remaining countries/regions (South Korea, Germany, the United States, Canada, Malaysia, Saudi Arabia, Indonesia and Iran) have relatively lower counts, with each showing a decreasing trend. Figure 16 clearly demonstrates the substantial difference in literature output between China and the other listed countries/regions.

From Figure 17, it can be seen that the Hong Kong Polytechnic University has the highest number of publications, approaching 4. The other institutions, such as Pusan National University, Politeknik ATK Yogyakarta, and the remaining listed universities, have relatively lower and more similar counts, which are below 2.

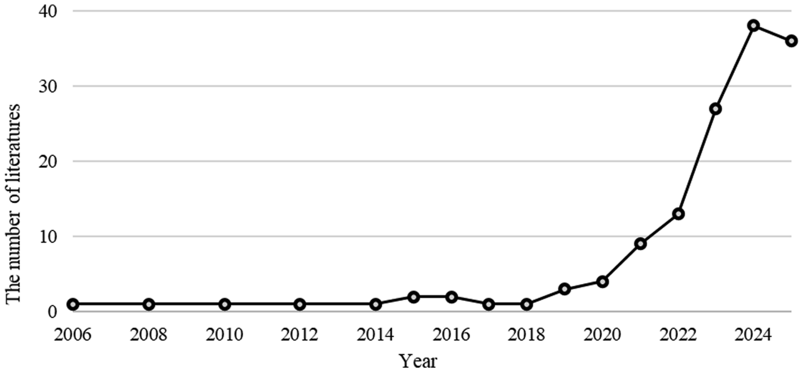


Figure 15. Trends of published papers using AI technologies in container ports

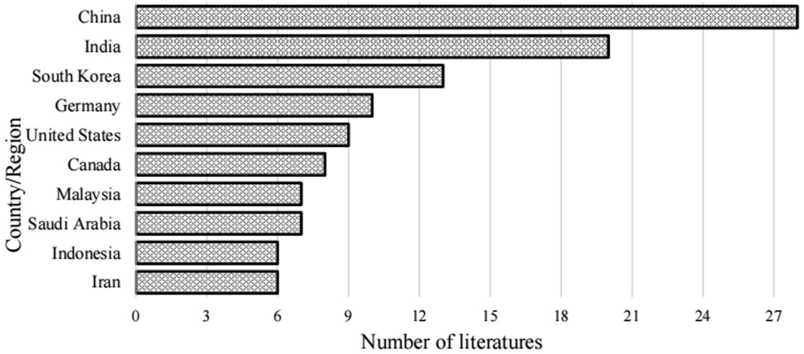


Figure 16. Literature related to AI by country/region

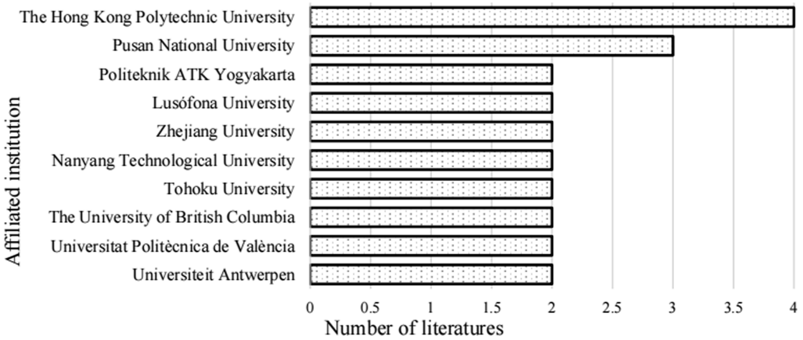


Figure 17. Literature related to AI by institution

It can be seen that the National Natural Science Foundation of China has the highest number of publications in Figure 18. The other financial sponsors have relatively lower and more similar counts, with most falling below 2. This chart effectively visualizes the comparative contribution of different financial sponsors to literature production.

4. Applications of AI for container ports

4.1 Terminal operation system

As the brain of the smart port, the Terminal Operation System (TOS) plays a vital role in the smart operation of ports. In addition to the famous TOS product, NAVIS, more and more container ports are developing their own tailored TOS for quick response to the new facilities and technologies. Some port facility suppliers, such as ZPMC in China, are also developing TOS products for broader market implementation. The characteristics of current TOS products worldwide can be summarized as follows.

(1) Integrated operation process framework with AI as the backbone. The TOSs with such an integrated framework are typically designed based on the container flow and port facilities. This framework enables facilities, such as AGV, QC and YC, to handle containers based on real-time information, which can improve the control precision of the automated facilities. Moreover, the TOS under the integrated framework can enable different facilities to cooperate on the same or different operational tasks by utilizing AI algorithms. Then, the waiting time of facilities could be significantly reduced, and a smoother workflow could be more available. For uncertainties, the

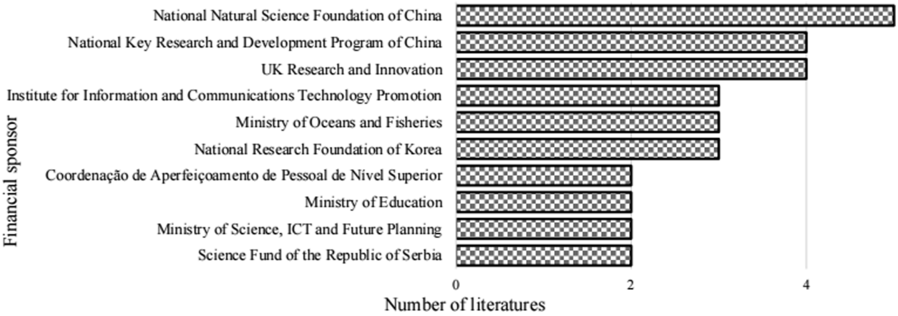


Figure 18. Literature related to AI by funding

TOS could modify the control and operation plan of the facilities based on real-time monitoring and data analysis.

(2) Coordinated resource management. The current TOS products aim to develop an operational plan based on the philosophy of coordinated resource management. Key port operational resources, such as berths, QC and yard space, are jointly considered when the TOS makes a plan. Under this centralized control mode, the TOS can provide planners with workload status for each operational period by real-time monitoring and dynamic analysis. Then, planners can make more rational and efficient resource allocation and scheduling decisions to ensure production efficiency and balanced operational load. Equipped with AI algorithms, the TOS could directly make and adjust operational plans by considering the overall performance of resource utilization and uncertainties.

(3) Integrated user operation interface. Due to the above two centralized control designs, planners require a more comprehensive view of the port. The current TOS products could feature a more user-friendly and highly efficient integrated user interface for operation. On the management side, the interface offers intuitive and easy-to-use functional modules, allowing users to easily formulate, view and adjust port operational plans. With real-time data updates and visual displays in the TOS, port planners can keep track of operational progress and plan execution at any time. On the control side, the TOS interface integrates functions such as equipment monitoring, remote operation and warnings. Planners can view the operating status and parameter information of equipment, perform remote operations and achieve precise control over equipment through the interface. Figure 19 illustrates the TOS interface developed by ZPMC.

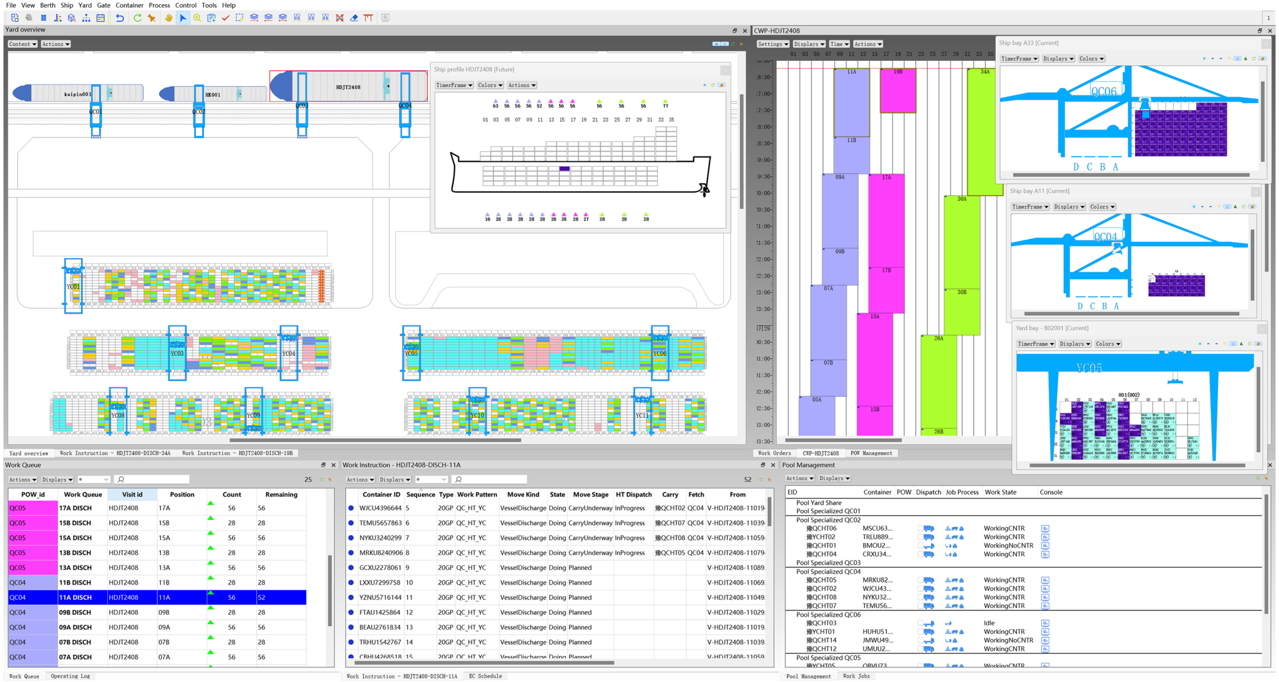
4.2 Prediction in container ports

Prediction is critical for container ports because it directly solves their core operational pain points and lays the foundation for efficiency, cost control and reliable supply chain service. The following content introduces the prediction of vessel arrival times, container dwell time, energy consumption and marine port accidents.

4.2.1 Prediction of vessel arrival time. Knowing the vessel arrival time in advance could help container terminal operators make better decisions, such as berth scheduling. Park *et al.* (2021) introduced reinforcement learning to identify potential vessel trajectories for predicting vessel arrival times. Ŝtepec *et al.* (2020) designed a machine learning method to predict vessel turnaround time. El Mekkaoui *et al.* (2020) developed neural network models for predicting the arrival time of vessels. In 2019, the Port of Rotterdam initiated the development of a self-learning computer model to predict vessel arrival times [8].

4.2.2 Prediction of container dwell time. Container dwell time refers to the duration a container spends within a container terminal. If a container is an import container, the container dwell time refers to the period during which the container remains in port after being discharged from a ship until it departs for delivery to a customer. Otherwise, if a container is an export container, the container dwell time denotes the time the container spends in port after being delivered to the port until it is loaded onto a vessel. Container dwell time is a crucial parameter for evaluating the performance of a container terminal, and minimizing dwell time is the primary objective for container terminal operators.

German port operator Hamburger Hafen und Logistik has successfully adopted a machine learning method to predict container dwell time. Kourounioti *et al.* (2016) employed ANNs to predict dwell time, considering various factors, including container size and type. An accurate prediction of dwell time could help container terminal operators make more informed decisions, such as determining optimal container stacking strategies (Maldonado *et al.*, 2019).



Work Queue

POW_id	Work Queue	Visit id	Position	Count	Remaining
QC05	**17A DISCH**	HDJT2408	17A	56	56
QC05	**15B DISCH**	HDJT2408	15B	28	28
QC05	**15A DISCH**	HDJT2408	15A	56	56
QC05	**13B DISCH**	HDJT2408	13B	28	28
QC05	**13A DISCH**	HDJT2408	13A	56	56
QC04	**11B DISCH**	HDJT2408	11B	28	28
QC04	**11A DISCH**	HDJT2408	11A	56	52
QC04	**09B DISCH**	HDJT2408	09B	28	28
QC04	**09A DISCH**	HDJT2408	09A	56	56
QC04	**07B DISCH**	HDJT2408	07B	28	28
QC04	**07A DISCH**	HDJT2408	07A	56	56

Work Instruction - HDJT2408-DISCH-11A

Container ID	Sequence	Type	Work Pattern	Move Kind	State	Move Stage	HT Dispatch	Carry	Fetch	From
WJCU4396644	5	20GP	QC_HT_YC	VesselDischarge	Doing	CarryUnderway	InProgress	豫QCHT02	QC04	V-HDJT2408-11019
TEMU5657863	6	20GP	QC_HT_YC	VesselDischarge	Doing	CarryUnderway	InProgress	豫QCHT07	QC04	V-HDJT2408-11039
NYKU3240299	7	20GP	QC_HT_YC	VesselDischarge	Doing	CarryUnderway	InProgress	豫QCHT08	QC04	V-HDJT2408-11059
MRKU8240906	8	20GP	QC_HT_YC	VesselDischarge	Doing	CarryUnderway	InProgress	豫QCHT05	QC04	V-HDJT2408-11079
GCXU2278061	9	20GP	QC_HT_YC	VesselDischarge	Doing	Planned				V-HDJT2408-11089
LXXU7299758	10	20GP	QC_HT_YC	VesselDischarge	Doing	Planned				V-HDJT2408-11069
YZNU5716144	11	20GP	QC_HT_YC	VesselDischarge	Doing	Planned				V-HDJT2408-11049
FTAU1425864	12	20GP	QC_HT_YC	VesselDischarge	Doing	Planned				V-HDJT2408-11029
BEAU2761834	13	20GP	QC_HT_YC	VesselDischarge	Doing	Planned				V-HDJT2408-11019
TRHU1542767	14	20GP	QC_HT_YC	VesselDischarge	Doing	Planned				V-HDJT2408-11039

Pool Management

EID	Container	POW	Dispatch	Job Process	Work State	Console
Pool Yard Share						
Pool Specialized QC01						
Pool Specialized QC02						
豫QCHT06	MSCU63...				WorkingCNTR	
豫YCHT02	TRLU889...				WorkingCNTR	
豫QCHT01	BMOU2...				WorkingNoCNTR	
豫QCHT04	CRXU34...				WorkingCNTR	
Pool Specialized QC03						
Pool Specialized QC04						
豫QCHT05	MRKU82...				WorkingCNTR	
豫QCHT02	WJCU43...				WorkingCNTR	
豫QCHT08	NYKU32...				WorkingCNTR	
豫QCHT07	TEMU56...				WorkingCNTR	
Pool Specialized QC06						
豫QCHT03					Idle	
豫YCHT01	HUHU51...				WorkingCNTR	
豫QCHT14	JMWU49...				WorkingNoCNTR	
豫QCHT12	UMUU2...				WorkingCNTR	
Pool Specialized QC05						

Figure 19. An interface of the ZPMC-TOS

4.2.3 Prediction of energy consumption. Predicting the fuel oil consumption of a ship's main engine is critical for the maritime industry, as it directly addresses core challenges of cost efficiency, operational sustainability, regulatory compliance and performance reliability. Peng *et al.* (2020) proposed machine learning–based models for predicting the fuel consumption of inland container ships, addressing the industry's need for accurate energy efficiency tools amid stricter emissions regulations and cost pressures. It emphasizes the use of easily accessible operational data to enhance the practicality of predictions, making the models applicable for real-world ship performance optimization. Gkerekos *et al.* (2019) employed machine learning to predict the ship's main engine fuel oil consumption, and they found that even simple models achieve a high level of fuel oil consumption prediction accuracy.

4.2.4 Prediction of truck traffic. Predicting truck traffic in container ports is a critical pillar of efficient, sustainable and resilient port operations. It directly addresses the unique challenges of container ports – where trucks act as the "bridge" between ships, yards and inland supply chains – and mitigates cascading issues that impact cost, time and environmental performance. Xie and Huynh (2010) focused on addressing the challenge of accurately predicting daily truck traffic volume at seaport terminals and introduced two kernel-based supervised machine learning methods to solve it. Nadi *et al.* (2021) introduced a data-driven, low-complexity model for short-term truck traffic prediction and validated its utility with real port data provided by the port of Rotterdam. They also provided tools to manage traffic around freight hubs, which directly support "green port" goals.

4.2.5 Prediction of container port accidents. Predicting container port accidents is crucial for safeguarding human life, protecting the environment, maintaining operational continuity and minimizing economic losses. Container ports are high-risk, high-throughput hubs where ships, cargo, equipment and personnel interact in complex, dynamic environments – making accident prevention a top priority. Atak and Arslanǒglu (2022) integrated terminal operating system data and historical accident reports to predict port accidents, addressing gaps in traditional safety approaches. They also identified critical accident-influencing features. Kim *et al.* (2021) recommended a "transfer learning" approach to adapt the model to different terminals for the prediction of container port accidents.

4.2.6 Prediction of container throughput. AI-driven container throughput prediction is a pivotal application in port logistics, leveraging advanced algorithms to forecast cargo handling volumes and address the inherent uncertainty of throughput fluctuations, enabling ports to implement data-driven operational and strategic planning. This technology has become indispensable as global trade expands and supply chains face increasing volatility, enabling ports to optimize efficiency, reduce costs and enhance resilience.

Core AI technologies powering throughput prediction include machine learning, deep learning and hybrid models. ML models – such as linear regression, random forests and gradient boosting frameworks – are widely used for short-term forecasts (daily/weekly). The practical value of AI-based throughput prediction is far-reaching. Operationally, it optimizes resource allocation: ports can adjust the number of active quay cranes, allocate yard storage space and schedule labor shifts in advance, minimizing idle equipment and reducing congestion.

4.3 Operations in container ports

Container port operations are a highly coordinated, multi-stage system that connects maritime shipping to inland logistics, enabling the efficient transfer, storage and distribution of containerized cargo. This section introduces the operation that uses AI methods.

4.3.1 Berth planning in container ports. Berth planning in container ports is a core operational process that allocates berth positions, docking times and related resources to container ships, aiming to simultaneously maximize berth utilization and minimize the duration of ship waiting. de León *et al.* (2017) developed a machine learning–based system for berth scheduling. Kolley *et al.* (2021) used a machine learning approach to optimize berth allocation considering robustness. Guo *et al.* (2021) proposed an efficient particle swarm optimization method integrated with machine learning to optimize berth allocation considering weather conditions. Mutlu *et al.* (2019) introduced a teaching-learning-based optimization method for dynamic berth allocation. Port operators have also begun to adopt AI technologies to enhance berth planning. Awake.AI, a software company, has already developed a berth planner system [9]. Berth scheduling is the process of assigning specific berthing positions to incoming ships and determining their arrival, berthing, loading/unloading and departure times. de León *et al.* (2017) developed a machine learning–based system for berth scheduling at bulk terminals.

4.3.2 Container relocation. Container relocation is a critical yet often underappreciated aspect of port operations, directly impacting yard efficiency, equipment utilization and the speed of cargo transfer between ships, trucks and trains. Hottung *et al.* (2020) proposed a deep learning heuristic tree search method to solve the container pre-marshalling problem. Zhang *et al.* (2020) introduced a machine learning–driven branch pruner for the container relocation problem. Jiang *et al.* (2021) designed a reinforcement learning base heuristic to solve the container relocation problem. Wei *et al.* (2021) also developed a reinforcement learning approach to solve the container relocation problem. Yan *et al.* (2024) developed a deep reinforcement learning algorithm to solve the container relocation problem.

4.3.3 Automated guided vehicle scheduling. AGVs are a core component of automated container port operations. Their scheduling refers to the process of assigning AGVs to tasks and optimizing their routes/timelines to minimize delays, maximize equipment utilization and reduce energy consumption. Hu *et al.* (2023) introduced a multi-agent reinforcement learning method to design the AGV path.

5. New technologies and future research

5.1 Next-generation port design and operation

The advent of mega-ships promotes container ports to boost their productivity levels. Usually, there are many technologies to improve their productivity: (1) buying additional automated equipment, such as a quay crane; (2) upgrading their current terminal operating system by using advanced algorithms, such as machine learning and (3) developing an advanced container terminal. Many countries, including South Korea, China and Singapore, have already introduced new policies to develop next-generation container ports, with the aim of accelerating their national economies. The container port is a complex system that involves various subsystems, including the berth allocation system, the quay crane operating system, the container truck appointment system (also known as the terminal appointment system), the storage systems, the AGV dispatching system, the planning system and the container yard planning and management system. With the increase in vessel capacity and container throughput, the capacity of modern container terminals is becoming increasingly larger, which in turn makes them more complex. Scholars and industries started to develop the next-generation container terminal, which needs a new container terminal operating system. Kim and Lee (2015) studied several decision-making problems in container terminals and explored the technological development trend for the advancement of terminal operating systems. Abou Kasm and Diabat (2020) proposed a novel quay crane scheduling model for next-generation container terminals.

Port automated equipment is very capital-sensitive. Buying additional automated equipment or developing advanced needs requires higher capital expenditures. For medium-sized container terminals, updating their existing system by using advanced technologies will be cost-effective and require fewer modifications. Recently, ZPMC proposed an intelligent horizontal fleet management system that can easily adapt to traditional port layouts with minimal infrastructure retrofit. This method has been successfully implemented in some ports in China for upgrading their systems.

5.2 Sharing port facilities and information in container ports

The outbreak of COVID-19 has presented the shipping industry with new challenges and depressed the container throughput at the majority of container terminals. COVID-19 intensifies the mismatch between supply and demand. The sharing economy is one method to reduce the costs incurred by lower container demand. The sharing economy is becoming increasingly popular and continues to grow. A traditional sharing method used in the maritime industry is vessel sharing, which is facilitated through a vessel sharing agreement. A container port has two types of facilities, including hardware and software facilities. Future studies of sharing facilities can be classified into two categories: sharing hardware facilities and sharing software facilities, such as sharing quay crane between different container terminals and sharing vessel arrival information between different container terminals.

5.2.1 Port facility sharing. Recently, scholars have started to propose facilities sharing at container ports. Jin *et al.* (2019) investigated storage space sharing at a container port among various container handling companies, marking the first study in the maritime industry to examine storage space sharing. Ma *et al.* (2020a) also studied facility sharing in the business-to-business model and gave a case study for the Hong Kong port. Both Jin *et al.* (2019) and Ma *et al.* (2020a) found that sharing facilities will reduce operating costs for container terminals. Future studies on sharing facilities could consider yard cranes and AGVs.

5.2.2 Information sharing. Another possible direction for sharing is data fusion among different subsystems of a terminal operating system. Integrating data from sensors and facilities at a container port will break through the information island. Data fusion gives an opportunity to make decisions from a data-driven perspective (Heilig *et al.*, 2020). Olesen *et al.* (2013) found that information sharing can improve the performance of container ports.

Awake.AI, a software company, launched a collaborative and open data platform in June 2020. Awake.AI is attempting to establish a smart port ecosystem by exchanging real-time data provided by maritime logistics actors. Participants on the collaborative and open data platform can improve their situational awareness, predictability and planning horizons. Figure 20 shows a user interface of a collaborative and open data platform provided by Awake.AI.

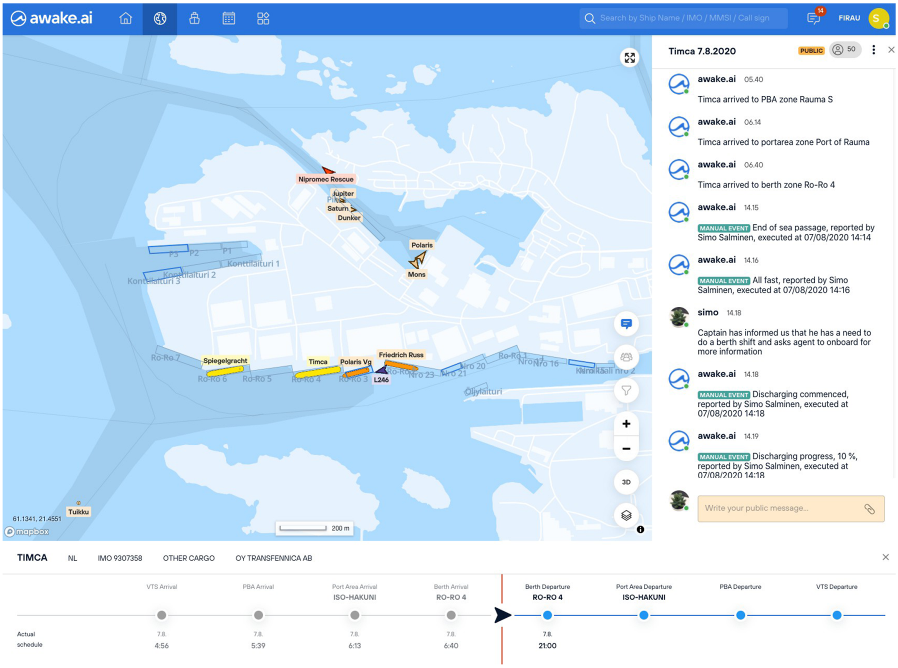
Shipping companies need to provide detailed information, such as depth, admission policy and arrival and departure times for the container port, to plan a port call effectively. Shipping and ports are collaborating by sharing information to create a safer, cleaner environment and lower costs for all partners.

5.2.3 Standardization in data sharing and documents. Standardization, which guarantees interoperability, is one of the keystones of any technology. Several projects, including the PortCDM concept, the UN/CEFACT Smart Container project and Port Call Optimization, have been launched to promote standardized data sharing. UNECE's white paper emphasizes that standardization is critical for smart containers to realize their full value [11].

5.3 Blockchain

Blockchain records the history of any data to make it unalterable and then distributes that data to make it transparent by using decentralization and cryptographic hashing. Although blockchain is a relatively new distributed ledger technology, invented in 2008, it gained significant popularity after its successful application in Bitcoin. There are many parties involved in shipping containers, and they need to interact by exchanging shipping documentation, such as container ID, size, type, gate-in date and timestamp. Blockchain enables the digitization of shipping documentation, thereby reducing intermediation among various parties. The Port of Rotterdam has proposed a blockchain-based project that can automate the release of containers to drivers, reducing transfer time.

Wang *et al.* (2020) proposed a blockchain-based framework to improve the efficiency of ship traffic in a port. Pu and Lam (2021) proposed a conceptual framework for blockchain adoption in the maritime industry. Bavassano *et al.* (2020) summarized the recently published papers related to blockchain in the shipping industry. Tsiulin *et al.* (2020) reviewed the



Timca 7.8.2020 PUBLIC 50

awake.ai 05.40
Timca arrived to PBA zone Rauma S

awake.ai 06.14
Timca arrived to portarea zone Port of Rauma

awake.ai 06.40
Timca arrived to berth zone Ro-Ro 4

awake.ai 14.15
MANUAL EVENT End of sea passage, reported by Simo Salminen, executed at 07/08/2020 14:14

awake.ai 14.16
MANUAL EVENT All fast, reported by Simo Salminen, executed at 07/08/2020 14:16

simo 14.18
Captain has informed us that he has a need to do a berth shift and asks agent to onboard for more information

awake.ai 14.18
MANUAL EVENT Discharging commenced, reported by Simo Salminen, executed at 07/08/2020 14:18

awake.ai 14.19
MANUAL EVENT Discharging progress, 10 %, reported by Simo Salminen, executed at 07/08/2020 14:18

Write your public message...

TIMCA NL IMO 9307358 OTHER CARGO OY TRANSFENNICA AB

	VTS Arrival	PBA Arrival	Port Area Arrival ISO-HAKUNI	Berth Arrival RO-RO 4	Berth Departure RO-RO 4	Port Area Departure ISO-HAKUNI	PBA Departure	VTS Departure
Actual schedule	7.8. 4:56	7.8. 5:39	7.8. 6:13	7.8. 6:40	7.8. 21:00			

Figure 20. A user interface of a collaborative and open data platform provided by Awake.AI [10]

blockchain-based applications in shipping and port management. According to the previous studies (Shi and Wang, 2018; Tsiulin *et al.*, 2020; Bavassano *et al.*, 2020; Clott *et al.*, 2020), the future research directions can be summarized as the following main issues: (1) digitalizing and easing paperwork could simplify paper process, such as digitize shipping documentation; (2) tracking and tracing of cargo information could avoid cargo fraud, and tracking and tracking navigation data will make the transportation more intelligent; (3) customs clearance and management; (4) standardization and platform development, such as energy management system (Kermani *et al.*, 2020), data utility platform; (5) business model and regulation, such as creating smart contracts to streamline trading processes.

Utilizing blockchains in maritime logistics can enhance shipping communications, secure data, facilitate asset certification and optimize shipping resources. Calculating blockchains is very energy-consuming. Regulatory measures to reduce energy usage need to be implemented for both cargo owners and stakeholders to promote sustainability [12].

5.4 Big data and IoT

Data generated by IoT is the foundation for AI (Zhang and Lee, 2023). Machine learning and deep learning need massive amounts of data for training models. Container terminal generates an enormous amount of data from the vessel, yard crane, quay crane, AGVs, container truck and sensors, including radar, lidar, inertial, radio-frequency identification (RFID), ultrasonic, eddy current sensors and cameras. Sensors are integrated into quay cranes, yard cranes, gates or other container terminal facilities, collecting data that can be used in position measurement systems for trolley positioning, gantry positioning, AGV positioning and spreader position measurement. Video cameras, sensors and RFID facilities are commonly used for AGV navigation in ports (Luo, 2019). Xiao and Ma (2020) developed artificial forces to prevent collisions between virtual autonomous ships by utilizing automatic identification system data.

Container ports generate a large amount of data from IoT, global positioning systems, RFID and traffic management systems. Terminal operating system. Big data can be used by intelligent algorithms to predict the behavior of equipment.

Cyber-physical systems are an extension of wireless sensor networks to a network of interacting physical inputs and outputs. Sensing and actuating parts of the network form an entity that must act and react autonomously and intelligently in response to its changing environment. Smart cities, smart production lanes and smart grid are examples of this new technological process. Since each environment has its own unique characteristics and challenges, a profound understanding of the surroundings is necessary. This requires cautious adaptation to the specific task, resulting in different implementations depending on the required application. The key to building cyber-physical systems is to view the problem as a sum of all significant aspects, rather than solving the problems separately.

5.5 Drones in port operations

A drone is a powerful tool for security and surveillance and can also be used to take draft readings and inspect holds on large bulk carriers. A drone can also be used for vessel traffic management by providing real-time physical monitoring of vessels, thereby offering consistent situational awareness to the controller. Drones are again being used for environmental policing. Drones armed with sensors and cameras can be used for environmental policing. A vessel requires replenishment of essentials upon arrival at a container port, which is typically accomplished by launching a delivery craft. Typically, launching a delivery craft increases the turnaround time. If the essentials are delivered by drones for the last-mile delivery, the delivery time could be reduced. A traditional port usually has a physical space for handling containers and installing port facilities. Once a port is constructed, it is very difficult to expand it. With the increase in container volumes, many ports have limited availability of berths.

5.6 The fifth generation mobile networks (5G)

The telecommunication industry plays an important role in port transformation (Gizelis *et al.*, 2020). The fifth generation mobile network (5G) offers faster and higher bandwidth compared to previous generation mobile networks, enabling prompt communication between sensors in a container port. 5G provides a mobile network with a high level of security, reliability and speed.

5G has many benefits in terms of mobility, coverage, uplink bandwidth, interference improvement and security compared with other information and communications technologies, such as Wi-Fi, fixed networks and previous generation mobile networks. One of the primary advantages of 5G is its real-time data transmission speed, which can be utilized in various facilities for efficient data transfer.

Automation operations of port facilities, such as quay cranes, have been studied by container terminal operators for many years to develop remote control systems. The emergence of 5G accelerates the development of automation operations in port facilities through its properties, including low latency, high bandwidth and high reliability. Unmanned cranes can be remotely operated by using 5G. Remote control of unmanned cranes provides a safer working environment for unmanned crane operators. By collaborating with Ericsson on 5G, Qingdao Port is upgrading its manually operated harbors to automated ones, thereby making operations more flexible and efficient. The telecom company LG Uplus and Seoho Electric, Korea's fourth-largest conglomerate and the world's second-largest port crane system developer, respectively, cooperated to develop a 5G network with automated port cranes (KoreaTechToday, 2019). The possible applications of 5G in container ports are listed as follows:

(1) Unmanned gantry cranes

(2) Unmanned quayside container cranes

(3) Cross-vehicle control of an intelligent guided vehicle

(4) Video surveillance and AI recognition

Video surveillance is very important during vessel access and the container operation process. Traditional security tasks in container ports focus on vessel detection, facial recognition of port staff, container monitoring and port access verification as well as access control, the prevention of workplace accidents in locks and the control of goods transit, among others. By using 5G, video surveillance and AI recognition perform an integral control of port areas and maritime spaces, optimizing all processes to avoid losses in profits.

5.7 Decarbonization in container ports in association with port digitalization

Container port decarbonization relies heavily on digitalization, which provides technical support across four key areas (Moeis *et al*., 2025). Energy management optimization utilizes IoT, big data and smart sensors to monitor the energy consumption of port equipment in real-time, identifying inefficiencies to enhance efficiency. Technologies like blockchain ensure real-time, secure info sharing among ports, shipping firms and customs, coordinating operations to shorten ship waiting times and lower emissions. Ports also use digital tools to promote green practices. Additionally, big data and cloud computing analyze large-scale operational and energy data to predict demand trends and inform scientific energy-saving plans. Overall, digitalization acts as a core enabler, integrating technology into energy use, operations, supply chains and innovation to help container ports reduce carbon emissions.

6. Discussions and conclusions

Many countries, originating from private companies, plan to develop next-generation container ports and aim to reduce emissions from the maritime sector. The next-generation container port should be a smart port and a green port simultaneously (Song *et al*., 2024; Lee *et al*., 2025). There is a lack of research that systematically and comprehensively examines the applications and impacts of AI on container ports. This paper, for the first time, investigated AI and smart ports from a new perspective. This paper summarizes the AI technologies adopted in container port operations and management by reviewing the development of AI and container ports, which helps facilitate the commercialization of AI for constructing a future container port. This paper has also provided stakeholders in maritime supply chains with insight into emerging trends in future container port development. Future research directions for next-generation container port development are also presented as follows:

(1) How to integrate the operation plan and facility control? Most of the current ports are making an operation plan and facility control independently via TOS and the Equipment Control System (ECS), respectively. For instance, when the TOS makes the QC and AGV dispatching plan, the ECS determines the detailed operational sequence of QC and the routing of AGVs. This gap between the two tiers of decisions may

result in congestion and waiting for facilities. By utilizing AI algorithms, researchers and practitioners can develop an approach that combines operational plans with facility control plans for improved overall port management.

(2) How to make a better port plan by cooperating with vessels? The port operation plan highly depends on the vessel plan, particularly for oceanic container vessels. As the size of a single vessel continues to increase, making shorter service times for vessels is becoming increasingly challenging for ports. Moreover, automated or unmanned vessels could become popular in the future. Then, the berthing and QC operation may be addressed under new conditions. Then, a new AI-controlled workflow between ports and

vessels could be essential, and new AI algorithms to coordinate vessel arrival plans and port operation plans could be beneficial from both research and practical perspectives.

(3) How to coordinate the transport network and supply chain? The cargo, vessels, hinterland transporters and information coverage at ports are hubs of the maritime transport network and supply chain. By utilizing AI algorithms and digital tools, ports can coordinate the various transport modalities and stakeholders to achieve a smoother logistics flow. For instance, AI algorithms may help supply chains match transport supply and demand, reducing logistics' costs and empty travel. The AI algorithm may also contribute to the new transport business, such as the containerization of bulk cargo.

(4) How to coordinate the operation plan and the new energy network? As green operations become increasingly popular in the real world, many ports are developing new energy networks that incorporate various types of energy sources, including solar power, wind power and bioenergy. However, the current practice has not fully integrated the power supply and port operation to achieve higher green performance. Because the supply of new energy can be uncertain due to weather and climate conditions, AI methods can help ports adjust their operation plans quickly, leading to better energy utilization and reduced costs. Therefore, the implementation of AI in this area could also be a fruitful direction for future study.

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Notes

1. https://amsterdamsmartcity.com/projects/smart-port-port-of-amsterdam
2. https://www.mardep.gov.hk/en/publication/portstat_archive.html and https://www.mardep.gov.hk/en/publication/portstat.html.
3. Figure source: http://www.casanova-hernandez.com/ch_projects/u_urbanism/chronology/u024
4. Figure source: https://www.box-bay.com/
5. https://www.mpa.gov.sg/web/portal/home/media-centre/news-releases/detail/ccceb28e-357b-4be5-9590-963ef053fb70
6. https://www.aminer.cn/
7. The data of this figure were collected from https://www.scopus.com/ with keywords (metaheuristics AND container port OR container terminal)
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