Cyber-Physical Integration for Future Green Seaports: Challenges, State of the Art and Future Prospects

Ying Lu[®], Student Member, IEEE, Sidun Fang[®], Senior Member, IEEE, Guanhong Chen, Member, IEEE, Tao Niu[®], Member, IEEE, and Ruijin Liao[®]

Abstract—To achieve the "carbon neutrality" target, multiple heterogeneous energy networks are integrated within seaport areas to form a special energy system with tight "transportation-energy" coupling, which brings massive information exchanges between different networks and therefore motivates the cyber-physical integration of seaports. This article first summarizes the activity clusters and the promising technologies for future green seaports. After that, the cyber-physical integration framework within seaport area is promoted and the typical operating strategies are overviewed. Then the physical models of seaport are provided with a solid literature survey. At last, this article proposes three key problems for the cyber-physical integration within seaport areas: the hybrid cyber-physical model in seaport, the economy of cyber-physical system in seaport and the resilience of cyber-physical system in seaport.

Index Terms—Carbon neutrality, cyber-physical integration, heterogeneous networks, seaport energy system, transportation-energy coupling.

I. INTRODUCTION

ARINE transportation, which undertakes 80–90% of global trade serves as a vital connection between the sea and the land [1]. With the growing demand for maritime transportation, energy consumption increased by 1.6% annually from 2000 to 2015, which generates about 3–5% of carbon emissions and 15% of nitrogen and sulfur oxide emissions [2], [3]. With "carbon neutrality" becoming the focus of the energy industry, energy saving and emission reduction have become the primary objective of marine transportation. As important hubs of marine transportation systems, seaports need to operate economically and environmentally in a sustainable way.

In the context of "carbon neutrality," each energy sector needs to develop its potential to improve energy efficiency. There are two common measures: 1) the utilization of alternative sources and 2) equipment-based energy-saving technologies.

The authors are with the Department of Electrical Engineering, Chongqing University, Chongqing 400074, China (e-mail: yinglu-cqu @foxmail.com; fangston@foxmail.com; cghrmzx@126.com; niutthu@ qq.com; rjliao@cqu.edu.cn).

Digital Object Identifier 10.1109/TICPS.2023.3283234

These energy efficiency improvement measures will also become the key technologies to achieve the green development of seaports. In October 2014, the EU Parliament signed an executive order requiring all maritime transport departments in the EU to achieve a renewable energy supply ratio of more than 27% and an energy efficiency improvement of more than 30% before 2030 [4]. Energy efficiency management ranked third among the top 10 technological bottlenecks in European ports [5]. In addition, since seaports are usually adjacent to coastal cities, the energy efficiency management of seaports not only has a relation to regional economic development but also impacts the environment through energy consumption, gas emission, and waste management [6]. Therefore, the sustainable development of seaports has gradually attracted the attention of local policymakers.

In land-based energy systems, energy efficiency is determined by the generation, transmission, storage, distribution, and transformation of energy flows. To achieve better efficiency performance, integrated energy technologies [7] have been developing rapidly in various fields in recent years, which start from the supply of integrated cooling, power and heating and then develop into complex systems such as gas, electricity, heat, and water. Nowadays, integrated energy technologies are widely used in industrial parks or residential communities and have shown great potential to re-shape the operating patterns of the future energy industry [8]. A similar development trend is also observed within seaport areas. At first, cold-ironing technology and electrification of ship and port equipment drive the reinforcement of the electrical network in seaport [9], then massive demands of cold-chain logistics bring the large scale of thermal loads [10], and last but not least, the supply of zero-carbon fuel (hydrogen, ammonia) brings liquid flow management for seaport. With the above, seaports can be viewed as special "marine integrated energy systems", which should properly coordinate multiple energy flows to achieve energy efficiency improvement [11], [12].

Besides the problem of managing multiple energy flows, the deep interdependence between energy and transportation is another issue for port integrated energy systems [13], since seaport should provide sufficient energy to meet multiple types of transport actions, such as berth allocation [14], quay crane (QC) scheduling [15], transferring vehicle scheduling [16], and

This work is licensed under a Creative Commons Attribution 4.0 License. For more information, see https://creativecommons.org/licenses/by/4.0/

Manuscript received 10 February 2023; revised 3 May 2023; accepted 30 May 2023. Date of publication 6 June 2023; date of current version 22 June 2023. (*Corresponding author: Sidun Fang.*)

intermodal transportation [17], which further derives the integrated energy and transportation system within seaport areas.

As above, the management of multiple energy flows and the coordination between energy and transportation are the utmost problems for the development of port integrated energy systems. However, the involved heterogeneous flows within seaport have quite different characteristics, i.e., control objectives, network structures and operating patterns, which makes the centralized control of port integrated energy systems beyond reality. In this sense, a decentralized control framework is necessary which brings enormous information exchange demand among different sub-systems, i.e., electrical, logistic, thermal and fuel sub-system [18], [19]. Those huge information exchanges require a strong, robust and efficient cyber-physical integrated framework for future seaports, which is the main focus of this article.

Some review articles related to green seaports have been published recently, to meet the goals of improving energy efficiency and reducing carbon emissions at ports. Reference [20] reviewed and analyzed operational strategies, use of technology, renewable energy, alternative fuels and energy management systems to improve energy efficiency and environmental performance at ports and terminals. Reference [21] aimed to systematically review and discussed the effects and problems of emission reduction measures adopted by different ports. Reference [22] Reviewed and classified technical and operational measures adopted by ports to reduce greenhouse gas emissions and improve energy efficiency. In Reference [23], the development of cold ironing technology were summarized, including its operation, power requirements, standardization, challenges and important evaluation indexes. Some review articles analyzed cyber-physical issues on the digital transformation of power systems into cyber-physical systems. Reference [24] and [25] summarized the vulnerability and resilience of the cyber-physical system, and proposed how to enhance the resilience of the power system. Reference [26] reviewed the network physical and network security systems, standard protocols and challenges of smart grid, and put forward the direction of the research on intelligent grid system applications in the future. However, to target the green port, the port integrated energy system faces new cyber-physical issues, such as the coordinated control of port logistics equipment, the port integrated electric-cold-transport management, the port information and the intelligent control. These topics are the subjects of our comprehensive reviews in this article. This article conducts a comprehensive review and discussion on the challenges, state of the art and prospects for formulating the cyber-physical system of port integrated energy systems. The contributions of this work are summarized as follows:

- We conduct a systematic overview of the cyber-physical framework of seaport integrated energy systems from the perspective of activity clusters, energy networks and cyber systems, based on the unique operational characteristics of seaports.
- We analyze control methods for seaport integrated energy systems, including multiple energy flow coordination, logistic activities, and integrated energy storage. The basic

mathematical models are reviewed with the analysis of key solution challenges.

3) We discuss the cyber-physical resiliency and provide a future roadmap to expand the studies on the port green communications, the hybrid cyber-physical model and the economy of cyber-physical systems in seaports, with the goals of superior quality of services and energy management efficiency of seaports.

To find the published research on the analysis of green seaports, databases including Web of Science, IEEE Xplore, ScienceDirect and Scopus were searched the following key words in title, abstract or author-specified keywords of published research:

- "port", or "seaport"
- "energy efficiency", "energy efficient", "energy management", or "energy system"
- "transport", "logistic", or "activity"

With further filter, as this article focuses only on English papers published in authoritative journals in the last ten years, papers meeting these criteria are chosen to be reviewed in this article. In this way, the authors are confident that the most important and influential papers on the analysis of green seaports that have been published in well-known databases have been captured in this review. Once the papers were filtered according to the aforementioned eligibility criteria, 176 papers were considered to be reviewed in this article.

Based on the unique operational characteristic of seaports, this article makes a comprehensive review and discussion on the challenges, state of the art and prospects for formulating the cyber-physical system of port integrated energy systems. The remainder of this article is organized as follows. Section II introduces the development of port integrated energy systems. Sections III and IV overviews the cyber-physical framework of port integrated energy system and formulates the key models of port integrated energy systems. Section V provides a discussion on the resiliency of seaport cyber-physical systems against cyber attacks and physical faults. The future roadmap and key problems are discussed in Section VI. Section VII presents the conclusions.

II. SEAPORT INTEGRATED ENERGY SYSTEMS

A. Activity Clusters

As a logistic centre, seaport has different clusters of activity and they generally lack coordination conventionally. With the development of seaport electrification, those activities can be co-dispatch to achieve better economic and environmental behaviours, and the resulted-in massive information exchange is the main motivation for the cyber-physical integration of seaports.

1) Quay Crane Operations: Quay crane, also known as a ship-to-shore crane, is an important equipment to complete the transport between ships and ports, as seen in Fig. 1. While ships berth in, QCs unload containers from ships or load containers onto ships. The scheduling of QCs is very important since the turnover time of ship berthing highly determines the operating



Fig. 1. Quay crane.



Fig. 2. Working area of seaport transferring vehicles.

efficiency of a seaport. Generally, a rate of 25 twenty-foot equivalent units (TEUs) per hour is the average level [27].

QC is one of the biggest power consumers at ports. Traditional QC operations are mainly powered by fossil fuels, like diesel and liquefied natural gas, and therefore produce massive emissions. Generally, as a large number of QCs hoisting simultaneously often bring pulse loads, limiting the number of QCs hoisting simultaneously can significantly reduce the peak power demand. However, average waiting and processing times will be therefore increased [28]. It is reported in reference [28] that allowing at most 84% of QCs hoisting simultaneously can reduce the peak energy consumption by 11.1% while increasing the processing time by 0.03% and waiting time for each container by 5.5 seconds.

The other issue for QC scheduling is the coordination with berth allocation, which can further reduce the turnover time of ships staying at the berth to unload and load containers. Berths of ships are determined in the berth allocation problem, while trajectories of QCs are determined in the QC scheduling problem. In reference [29], the models of integrated berth and QC management are reviewed, which can improve the overall efficiency.

2) Horizontal Operations: Horizontal operations transfer the cargo between the ships and the stackyards, mostly undertaken

by the transferring vehicles, as shown in Fig. 2. Horizontal transport vehicles are generally trucks, AGVs (Automated Guided Vehicles), etc. The operation efficiency of transferring vehicles is critical for the overall seaport efficiency. The operation of transferring vehicles needs to be physically constrained by other logistics equipment. As a result, In the job scheduling of transferring vehicles, it is necessary to reduce the empty driving of transferring vehicles as much as possible under the physical constraints of other logistics equipment [30]. Conventional vehicles in seaports are usually powered by fossil fuels, which bring many carbon emissions. In the carbon emission data of the Port of Los Angeles in 2019, the carbon emissions of transferring vehicles accounted for about 42.9% of the total emissions of the seaport [31]. Hybrid transferring vehicles [32], all-electric transferring vehicles [33], and hydrogen transferring vehicles [34] have become the main design trends to reduce the corresponding carbon emissions. Studies have shown that hybrid vehicles can reduce carbon emissions by more than 66%, while all-electric transferring vehicles can reduce carbon emissions by more than 90% [35]. The emission reduction effect of transferring vehicles depends on the energy resource. If it is produced entirely from renewable energy, the emission reduction effect can be up to 90%.

When scheduling the transferring vehicles, the vehicles should at first optimally match the transfer jobs. The transfer efficiency of the seaport transportation system is largely influenced by vehicle-job matching decisions. The optimal matching needs to ensure that the empty travel distance of vehicles is at a low level. Furthermore, different vehicle-job matching schemes make vehicles have different status constraints and routing constraints, for example, 1) job-picking nodes and jobdropping nodes determine where the vehicle starts and ends [36], 2) job expected finishing time limits the latest time to reach the destination [37], etc. Depending on these constraints, the charging/refuelling decisions will be affected, including charging/refuelling time and charging/refuelling demands. The vehicle scheduling decides when and where the vehicles should drive. Based on the job list, completing the transfer job within the specified time is the main goal of the transferring vehicle, and the transferring vehicles also need to ensure sufficient battery charge to complete their assigned job. To ensure safety, the vehicle cannot charge when loaded [16]. Therefore, the vehicle routing problem considers whether to go to a specific station to charge or continue with the next job after completing one.

3) Reefer Areas: The reefer area of the seaport is to store cold-chain containers, which mainly store fresh products. According to [38], typical cold-chain transportation is shown in Table I. Cold-chain transport containers are usually divided into two types: 1) Cold-chain transport containers with automatic temperature control system as a kind of "mobile refrigerator", shown in Fig. 3. This type of container needs external electrical power to maintain internal temperature. 2) Cold-chain transport containers without an independent temperature control system, which requires temperature control from the seaport. The proportion of the above two types of containers is 8:2. To optimally provide energy to the second type of cold chain transportation

Cargo	Temperature (\circ C)	Range $(\circ C)$
Deep freeze: Seafood	$-30 \sim -28$	[-2,2]
Frozen: fish, meat	-20 \sim -16	[-2,2]
Refrigerate: fruit, vegetable	$-5 \sim 5$	[-0.5, 0.5]
Medicine	$2 \sim 8$	[-0.1, 0.1]
Banana	$12 \sim 14$	[-0.2, 0.2]
Precision components	$18 \sim 21$	[-2,2]

TABLE I TYPICAL COLD-CHAIN TRANSPORTATION



Fig. 3. Cold-chain transport container.

Fig. 4. Yardstack.



Fig. 5. (a) Pipe transport and (b) belt transport.

container, ports need to develop an energy management strategy in reefer areas.

The temperature of reefer areas needs to be controlled by the seaport's energy management centre. In recent years, cold chain transportation develops rapidly, and the energy demand from reefer areas becomes the main load demand within ports [39]. According to the United Nations Conference on Trade and Development statistics, the cold chain transport industry worldwide maintained an average growth rate of 20% from 2000 to 2020, annually [40]. Reference [41] points out that in the seaport of Valencia, Spain, cold chain transport consumes 45% of the total energy demand of the seaport, which has become the largest energy demand in the seaport area. Reference [42] proposed a hierarchical control scheme for reefer containers, which contains the day-ahead and intra-day modules, representing a rough and fine-tuning strategy, respectively. Reference [43] clarifies the effect of reducing reefer container energy consumption by installing roof shade. However, there are still few works studying the energy management of reefer areas from the perspective of the whole port.

4) Hinterland Transportation: Cargo is transported from/to the seaport area by hinterland transportation, including road and rail transportation. The yardstack is an important area connecting hinterland transportation and ports, as seen in Fig. 4. Important logistics equipment in the yardstack is the yard crane, like rubber tired gantries (RTG) and rail-mounted gantry cranes (RMG), which are utilized to transfer cargo within a yard or between the yard and the hinterland transportation [44]. Optimal yard crane scheduling can reduce the waiting time and congestion of hinterland transportation, thus speeding up the efficiency of cargo in and out of the seaport. However, current yard cranes, especially for RTGs, are powered by diesel fuel, which brings great gas emissions and conflicts with the development of green ports [45], [46]. The electrification of yard cranes is therefore widely expanding around the world, which leads to the energy-transport scheduling for yard cranes. Additionally, in inland transportation, the arrival time of rail or external trucks to the seaport yard stack provides constraints for yard crane scheduling. To reduce carbon emissions, the optimal yard crane scheduling strategy determines the yard crane movement trajectory and loading and unloading operations.

5) Others: With the increasing worldwide demand for large liquid and dry bulk cargo, the seaports also put higher requirements on the handling and transmission system of liquid and dry bulk cargo. There are three main types of liquid cargoes: oil (bulk crude oil and refined oil), liquefied gas (liquefied natural gas and liquefied petroleum gas), and liquid chemicals (such as ether, benzene, alcohol, acid, etc.). Iron ore, coal, and grain (such as corn, soybean, and wheat) account for about 61.5% of the total seaborne trade volume of dry bulk cargo, which has the greatest impact on the transportation of dry bulk cargo, while the belt transmission system transfers liquid cargo, as shown in Fig. 5.

Both the pipeline transmission and the belt transport systems bring quite a few challenges to the construction of the seaport. In addition to transportation, fuel pipelines can use clean fuels to power the seaport to achieve the goal of green ports. The physical and chemical properties and management methods of various types of liquid cargo are different, so the seaport needs to study the construction and operation strategies of different liquid cargo pipelines. For example, in liquefied natural gas pipelines, due to the volatile nature of liquefied natural gas, it is necessary to balance the air pressure through the equipment [47]. In addition, some liquid cargoes must be stored/transported at low temperatures, such as liquefied natural gas [48]. The energy consumption of belt conveyors has always been the focus of industrial network research. Therefore, the planning and operation strategy of pipeline and belt transmission systems will become the focus of port construction in the future.

B. Promising Technologies

To reduce carbon emissions within seaport areas, many promising technologies are about to incorporate, which are the main resources to support the cyber-physical integration of seaports.

1) Renewable Energy Integration: Due to geographical advantages, renewable energy resources available at the seaport include solar, wind, ocean, and geothermal energy [49]. Renewable energy integration in ports has been discussed in detail in reference [50]. In academic research, reference [51] has studied the penetration rate of renewable energy as an important evaluation index of ports.

In practical projects, many ports developed projects on integrating renewable energy. Solar panels can be built on vacant ground in ports or rooftops of wharf-related buildings and warehouses. In 2016, Singapore invested \$30 million to build a PV plant on top of the seaport's storage cargo warehouse, with a maximum grid-connected power of up to 9.8MW [52]. The US Port of Houston uses Spilman's island to plan a PV plant to power the seaport area [53] directly. Wind energy is abundant in coastal areas, and there is a natural advantage to building wind power turbines in ports, many of which are equipped with onshore and offshore wind turbines, but space availability can also limit wind power. In 2017, the Port of Hamburg installed 27 wind power units with a grid-connected capacity of up to 40 MW [54]. Ocean energy, including tidal energy, mainly utilizes the kinetic energy generated by tides near the shore of straits, islands, and channels. The Port of Valencia in Spain uses the coastal breakwater dam to build a tidal energy power station. The breakwater is about 500 m long, with a total installed capacity of 2.5 MW [55]. Geothermal energy uses energy stored in the Earth's strata. Port of Rotterdam, Netherlands's port authority started the geothermal energy project in 2017 [53].

2) Multi-Energy Management: In the future, ports will become multi-energy systems, with the power network as the backbone to provide energy for port equipment and transferring vehicles [56]. Besides the power network, the heat and fuel networks will also be gradually integrated into the seaport multi-energy systems. The heat network takes cold chain transportation as the main service demand, while the fuel network works for various fuel management, storage, and transmission types. The overall structure of the future port integrated energy system is shown in Fig. 6, which includes four main types of energy networks: power network, heat network, fuel network, and transportation



---> Power flow ---> Heat flow ---> Natural gas flow ---> Vehicle flow

Fig. 6. Structure of port multi-energy system.

TABLE II ENERGY EFFICIENCY OF RTG AND E-RTGN

	Energy consumption	Price	Emissions
RTG	2.21L/ time	64048\$/ year	5.96kg/ box
E-RTG	3.02kWh/ time	8621\$/ year	1.92kg/ box

network, where a natural gas network is taken as an example of a fuel network. Multi-energy systems couple different types of energy.

In addition to these energy networks, other types of energy, like hydrogen, ammonia, and biomass, are utilized within ports, integrated by different energy conversion equipment. Biomass from ports or ships can be converted into biogas or biofuel, a cleaner fuel than traditional fossil fuels and can be burned to generate heat and electricity [57]. Hydrogen and ammonia energy are zero-carbon fuels that can be used to supply ships or vehicles. Hydrogen energy networks have been constructed in many ports to flexibly transport and store hydrogen energy. For example, Hamburg has built a hydrogen energy port, serving as the future base for developing hydrogen energy in Germany. A 60 km hydrogen network will be built and work with the existing liquefied natural gas network to supply green energy for large industries in Hamburg. In the future, as wind farms in northern Germany are further expanded, wind power that cannot be connected to the grid will be made into hydrogen and transported in Hamburg through marine transportation [58]. In reference [59], the Moroccan port was taken as an example to study the preparation of ammonia from desert photovoltaics for direct application in shipping.

3) Port Equipment Electrification: Electrification is widely used in cargo-handling equipment such as cranes in seaports. In reference [60], super electric containers reduce the maximum load of QC from 1211 kW to 330 kW. In reference [61], the maximum load of QC is reduced from 1500 kW to 150 kW. According to Table II, the energy efficiency of electrified RTG (E-RTG) is much higher than that of RTG. The operation cost and carbon emission of E-RTG are only 13% and 33% of that of RTG, respectively [20]. In addition, batteries are often used in cargo-handling equipment. For example, battery-powered forklifts, rail hauliers, and stacking cranes have been widely



Fig. 7. Integrated energy flows within seaport territory [56].

used in ports such as the San Pedro Bay port in the United States and the container terminal in Kaohsiung, Taiwan. Overall, electrification of the above port equipment can save about 30% of the total energy consumption, efficiently reducing greenhouse gas emissions [20]. In addition, port equipment supplied with hybrid power is composed of fossil fuel and electricity power generation. The effect of emission reduction transferring vehicles depends on the source of supplied energy. Hybrid transferring vehicles can reduce carbon emissions by more than 66%, while fully electric transferring vehicles can reduce carbon emissions by more than 90% [20].

Currently, the energy system of major ports worldwide has been electrified to varying degrees [62]. By 2020, Singapore's Jurong Port has been fully electrified, with all port equipment powered by electricity. Hybrid transferring vehicles have already been utilized, while fully battery-powered transferring vehicles have been analyzed for the feasibility of utilization [63]. The Yangshan Port have all been electrified, and some seaport areas have begun unmanned operations.

III. CYBER-PHYSICAL FRAMEWORK OF SEAPORT INTEGRATED ENERGY SYSTEMS

A. General Structure of Seaport Energy Systems

As above, seaport integrated energy system involves four types of energy networks, shown in Fig. 7 [56].

- *Power network:* The port energy system receives electricity from the main power grid, wind farm, photovoltaic station, etc., then supplies the seaport control centre, transfer vehicle, electrified equipment and cold-ironing power, oil refining, and battery storage.
- *Heat network:* Electric heating generations, such as Combined Cooling, Heat, and Power (CCHP) generations, are flexible backup power sources to generate electricity while providing energy for temperature control in the cold-chain logistic and fuel transportation.

- *Fuel network:* The port fuel network receives fuel from seagoing ships, which is processed and transmitted to external fuel pipeline networks in refining and storage areas.
- Transportation network: Transfer vehicles receive cargo from the sea and transfer them to hinterland transportation systems.

The objective of the seaport energy system is to reduce the total cost under the constraints of the shore side and ship side. In the power network, the system operators need to dispatch flexible power resources, including the start-stop and output states of generation units, the charging of electric vehicles, and the charging and discharging of energy storage, etc. In the heat network, the system operator needs to maintain the temperature and pressure of the nodes in the heat network to satisfy heat and cold demands. In the fuel and transportation networks, system operators need to schedule pipeline, vehicle, and road resources to meet fuel and cargo transportation requirements.

As above, heterogeneous networks are coordinated together within the seaport area. However, different networks have diversified decision variables, and maybe opposite characteristics, i.e., continuous or binary, linear or non-linear. Therefore it is rather difficult to achieve the global optimum of such a complex system via conventional centralized control. In this sense, a decentralized control framework via cyber-physical integration should be a better way which relies on massive information exchange between heterogeneous network meanwhile each subnetwork still utilize localized control.

B. Framework of Cyber-Physical Integration

Extended cyber infrastructure and software platforms that break through information barriers among separate subsystems play a crucial role in realizing the interoperable and compatible operation of heterogeneous physical subsystems in a future green seaport. With the rapid development of the Internet of Things, Big Data, and Mobile internet, cyber-physical integration in port integrated energy systems has been achieved considering the interaction between network information flow and energy flow [64]. Reference [26] reviewed energy systems' cyber-physical systems, including the cyber/information protocols and constraints. Fig. 8 shows a port integrated energy system under the background of cyber-physical integration. The cyber-physical system of a port integrated energy system can be divided into a physical system, and a cyber system (sensor units, communication units and control units).

- *Physical system units:* With the help of energy coupling technology and physical interconnection between different energy resources within seaports, port integrated energy system is the collection of generation, conversion and consumption of different forms of energy to ensure economical and efficient utilization [65].
- *Sensor units:* Sensors and devices sense system statues and physically communicate through the communication units, monitoring important data like values of voltage, current, states of a circuit breaker, and frequency [66].



Fig. 8. Seaport integrated energy systems in the framework of cyberphysical systems.

- Communication units: With different actual demands and required designs, the communication system would be wireless or wired. Communication appliances in communication systems include switches, Wi-Fi, routers, communication mediums, and broadband connection [67].
- *Control units:* Control units first analyze the system state obtained from communication units and then decide to operate the port integrated energy system. Next, the control signals are sent to different appliances through communication units. Control units centrally manage port integrated energy systems in different physical conditions.

Cyber-physical integration could be essential in developing the traditional seaport transportation system into the port integrated transportation-energy system. However, similar to other cyber systems, a significant disadvantage cannot be ignored for the port integrated transportation-energy system, which is cyber-security issues [26]. Cyber-security ensures the confidentiality of seaports, which is critical for protection, energy management, communication infrastructures, and operation. The seaport data, like consumer information, berth information and cargo information, are most important for authorities and seaports, which must be protected and keep privacy by cyber-security systems from unallowed access and disclosure.

C. Typical Operating Strategies

With the cyber-physical integration in seaports, the following typical strategies can be easily achieved to facilitate the operation of seaports.

1) Multiple Energy Flow Coordination: The traditional land integrated energy system consists of electricity, gas, and heat networks, while the port integrated energy system consists of electricity, heat, and liquid networks. The modelling of port electric and heat network is similar to that of the land energy network [68]. Unlike the gas network in the land integrated



Fig. 9. Storage and transmission of liquefied natural gas [69].

energy system, the introduction port liquid network is to transport liquid cargoes in the port area, including fossil fuels such as crude oil and liquefied natural gas or chemical feedstocks such as ammonia and hydrogen. These liquids can be divided into two categories according to whether they are produced in the seaport area: transport-type liquid and production-type liquid. Most transport-type liquids, like crude oil and liquefied natural gas, are transported from the ship to the port, while most production-type liquids, like ammonia and hydrogen, need to be produced in port areas.

For the liquid network of transport-type liquid, Fig. 9 takes the storage and transmission of liquefied natural gas (LNG) as an example to introduce the seaport liquid network operation mode [69]. There are two types of operation modes in Fig. 9: 1) LNG unloading mode (ship-to-port) and 2) LNG transmission mode (port to external transmission system). In the LNG unloading mode, LNG loaded on the ship is input into the storage (blue line). In LNG transmission mode, the equipment pumps both liquefied natural gas and natural gas, while the natural gas is reliquefied through a compressor, and the excess natural gas is processed through combustion equipment (red lines). Then, it goes through the liquid pump, turns the LNG into natural gas through the evaporator (blue lines), and then goes to the external network (red line). Furthermore, the conversion process of energy flow, such as electrolysis for hydrogen or ammonia production, can be modelled based on land P2G equipment [70].

In addition, integrating multiple energy flows will bring differences in time scale. For example, the transmission dynamics of heat and fuel networks are slower than that of the power network. Therefore, it is necessary to model multi-energy flow with multiple time scales. Reference [71] studied multi-time scale modelling problems and proposed the fourth-order quasi-steady state modelling method.

2) Energy Scheduling for Logistic Activities: As an important transportation hub, the seaport is the core of the connection between marine and land transportation systems, and its transportation management directly affects the operation efficiency of the transportation system. From ship berthing to leaving time, the port must complete the following operations.

- *Berth scheduling:* When a ship berths at the port, the port allocates berths and berthing hours for the ship, which must meet the operational constraints such as ship length, draft, number of berths, maximum cold-ironing power, maximum cargo handling efficiency, etc [72].
- Port equipment scheduling: After finishing berthing, the port must allocate loading and unloading equipment for cargo handling. Quay crane is used for cargo handling [72]. A belt conveyor is used for dry bulk cargo handling [73]. Liquid cargo is transferred into the storage equipment through a pipeline [69]. Operational constraints include the total amount of cargo, total handling time, etc.
- *Cargo transfer scheduling:* After the cargo is transferred from the ship to the port, it is necessary to schedule transferring vehicles to transport the cargo from the ship side to the yard side. Operational constraints include job scheduling, optimal route, and fleet size [74].
- *Yard scheduling:* Cargo transported to yards by transferring vehicles is optimally distributed and stored through the yard crane. Operational constraints include job scheduling and optimal route within yards.
- *Cold chain management:* Cold chain management is a special yard management problem in ports, considering integrated electricity-heat constraints and the temperature control of containers.
- *Multimodal transport scheduling:* As the port is an important connection between sea and land transportation, the seaport cargo must be transported to the external system by an external transportation system. This part of the management mainly involves the joint water-rail-road scheduling problem [75].

3) Integrated Energy Storage: In port areas, with the uncertainty of both energy supply and demand, developing energy storage technologies can balance the microgrid to achieve a good match between supply and demand. Storage devices can store energy during peak shortage periods or low tariff periods and provide power during peak load periods or high tariff periods. In addition, storage devices can provide frequency regulation for power networks. Existing physical energy storage technologies face high costs, erratic charge/discharge cycles, lifecycle issues and optimal sizing. Therefore, advanced mechanisms are needed for ancillary services. Virtual Energy Storage Systems (vESS) can be combined with traditional physical energy storage system to serve port energy system for economic objectives. As a result, both physical and virtual energy storage is needed in ports to provide flexibility for energy management.

- Physical Energy Storage: Electric energy storage, also called electrochemical energy storage, includes the conversion reaction between chemical and electric energy. For thermal energy storage, energy can be stored as hot water for later usage. Hydrogen storage converts electricity into hydrogen by electrolysis and stores it.
- Virtual energy storage: In addition to traditional electrical and thermal energy storage, fuel transfer/storage systems, electric vehicles, and temperature-controlled loads can also be considered special energy storage to provide flexibility in port areas. Mechanical storage, which uses kinetic

or gravitational energy to store electricity, can also be seen as virtual energy storage. Reference [76] used integrated electric-heat scheduling to achieve VESS in heat networks. The gas transmission has a similar energy storage potential in the integrated electric-gas system. Reference [77] proposed an integrated electric and thermal energy storage as an integrated VESS, considering the charging management of electric vehicles and thermal energy storage.

IV. MODELS OF SEAPORT ENERGY SYSTEMS

A. Models for Multiple Energy Flow Coordination

1) General Models: As a special integrated energy system, the port integrated energy system has considerable similarity with the energy side of the traditional land integrated energy system, which generally contains electricity, heat and gas flows [78]. As energy flows of electricity and heat have similar operational characteristics to land energy systems, the modelling of electricity and heat flow can be directly applied to port energy systems. Therefore, some of the flexible resources on the port energy side can be modelled using the current methods in land integrated energy systems.

The characteristics of the port integrated energy system are mainly reflected in the gas system. In land integrated energy systems, the gas system generally stands for natural gas and relies mainly on gas pipelines [78]. In contrast, in port areas with many fuels and bulk commodities, natural gas is mainly transported in compressed liquid form and regasified for input into external pipelines. For example, LNG arrives in port as a liquid and is transformed into a gaseous state when imported into external pipelines [79]. Therefore, many types of natural gas and multiple "gas-liquid" conversion equipment are the basic characteristics of ports. However, the modelling approach for port natural gas systems needs further investigation.

2) Energy hubs/circuits: Compared to electricity, heat, gas and liquids are characterized by slow transmission speed, high inertia and a certain delay in the transmission process. Therefore, they can be used as "energy storage" to provide flexibility to energy systems. In integrated electricity-heat systems, reference [80] investigated the flexibility that heat networks can provide as "energy storage". In reference [76], an electricity-heat dispatch model was proposed considering the heat network as a virtual energy storage system. In integrated electricity-gas systems, gas transportation also can provide flexibility as "energy storage". The analysis showed that the electricity-gas operation could diminish the uncertainty of renewable energy generation. The study of the energy network as "energy storage" in port integrated energy systems still deserves attention. In particular, the "gas-liquid" coupling in the port integrated energy system impacts the energy pipeline's "energy storage" characteristics. Taking LNG as an example, a typical modelling approach for the "gas-liquid" coupling characteristics of port integrated energy systems is presented, as shown in Fig. 10.

In Fig. 10(a), the liquid cargo discharged from the ship is first injected into the seaport fuel network through the liquid pumping equipment and then stored and transmitted in the fuel network. The Darcy-Weisbach fluid transport constraint was



Fig. 10. Liquid network topology of seaport.



Fig. 11. "Gas-liquid" pipeline model in ports.

used to model the fuel network [81]. It is important to note that Boiled-off gas (BOG) needs to be compressed into a liquid state using a liquefaction unit (consuming energy to compress the gas) and then returned to the storage facility and then connected to the external network through a regasification unit (consuming energy to gasify). In this process, the "liquid-gas" conversion process in the fuel network is used as an energy storage device. In addition, the fuel streams used for production or use in the seaport area, usually including various types of zero-carbon fuels, are connected to the electrical and heat networks through various P2G and fuel cell equipment. Therefore, as shown in Fig. 10(b), energy conversion modelling is also required. The modelling of the "gas-liquid" coupled piping is shown in Fig. 11. For exemplary illustration, a model with liquid and gas piping connected by an evaporator is chosen, and a complex piping network model can be referred to [82]. The time length during operation is T with the granularity of t.

Without pump:
$$h_f^t - h_t^t \le F_{ft}(q_l^t)^2, \forall t \in T$$
 (1)

With pump:
$$\begin{cases} (0 \le h_t^t - h_f^t \le -A(q_l^t)^2 + Bq_l^t + C \\ P_{pump}^t = k_{pump}(h_t^t - h_f^t)q_l^t, \forall t \in T \end{cases}$$
(2)

Without compressor: $(p_f^t)^2 - (p_t^t)^2 = G_{ft}(q_g^t)^2, \forall t \in T$ (3)

With !compressor :
$$\begin{cases} p_f^t \le p_t^t, \forall t \in T\\ P_{\text{comp}}^t = k_0 + k_1 \left[\left(\frac{p_t^t}{p_f^t} \right)^{k_2} - 1 \right] \end{cases}$$
(4)

$$\begin{cases} (1 - \eta_{loss})k_n q_l^t \Delta t = \frac{p_f^t(q_g^t \Delta t)}{RT}, \forall t \in T \\ P_{vapor}^t = k_{vapor} q_l^t \Delta t, \forall t \in T \end{cases}$$
(5)

$$\begin{cases} (0 \le h_f^t, h_t^t \le h_{\max}) \\ 0 \le q_l^t \le q_l^{\max} \\ 0 \le p_f^t, p_t^t \le p_{\max} \\ 0 \le q_q^t \le q_q^{\max} \end{cases}, \forall t \in T$$

$$(6)$$

The liquid pipeline model has different models depending on whether there is a liquid pump on the pipeline or not. Constraint (1) is a pipeline model without a liquid pump, while Constraint (2) is a pipeline model with a liquid pump. When the liquid pipeline has no liquid pump, the head at the starting point and end point follows the Darcy-Weisbach fluid transport constraint, which means that the head loss is proportional to the squared flow [81]. When the liquid pipeline is installed with a liquid pump, the head variation can vary between $[0, -A(q_l^t)^2 + Bq_l^t + C]$, where A, B, C are parameters. And the power P_{pump}^t consumed by the liquid pump can be calculated according to the head variation and flow rate, which k_{pump} is a parameter determined by the efficiency of the liquid pump. According to reference [83], the gas pipeline model also has different models depending on whether there is a compressor on the pipeline or not. Constraint (3) is a model without a compressor, while Constraint (4) is a model with a compressor. Where G_{ft} represents the pipe loss coefficient, k_0, k_1, k_2 are the coefficient parameters of the compressor, and p_{comp}^{t} is the power consumption of the compressor.

With the evaporator loss rate η_{loss} , the liquid and gas phases should satisfy the material balance constraint (5). Where, k_n represents the evaporation constant, R represents the standard gas constant, T is the Kelvin temperature. k_{vapor} represents the power constant of the evaporator. P_{vapor}^t is the evaporator power. Constraints (6) are upper and lower bound constraints for the variables involved in the model, including liquid flow head and liquid flow rate, gas air pressure and gas flow rate.

The gas and liquid phases are coupled by the evaporator's material balance constraint (5). Both the gas and liquid phase constraints are nonlinear and need to be transformed to solve. Note that the above model assumes that "gas" and "liquid" are within the same time scale. In general, the transmission speed of "gas" is faster than that of "liquid", so the time constant is shorter, and the modelling time scale for "gas" can be shortened in more refined modelling. Taking the variables of "gas" and "liquid" (node point h and node pressure p) as an example, the idea of multi-timescale modelling is to set sub-moments i at any moment t, and the corresponding head and pressure variables can be defined as h^t , $p^{t,i}$. These variables still follow the constraints of (1)–(6) to model energy pipelines at different time scales.

B. Models of Logistic Activities

According to the operation process, the seaport first schedules berths to ships (berth scheduling), schedules QCs for cargo handling (QC scheduling), schedules yard cranes and transferring vehicles for cargo transfer (yard crane scheduling, transferring vehicle scheduling), and finally transfer cargo to external transportation systems (intermodal transportation scheduling). Generally speaking, the transportation constraint ensures that the total transfer job is completed within the specified time.

TABLE III TIME SCALE OF LOGISTIC ACTIVITIES IN PORT AREAS

	Time scale	
Berth scheduling	Some days ahead or some weeks ahead	
Intermodal transportation scheduling	Some days ahead or month ahead	
Quay crane scheduling	Day ahead	
Quay crane scheduling	Day ahead	
Vehicle scheduling	Day ahead	
Yard crane scheduling	Day ahead	
Cold chain scheduling	Hour ahead	



Fig. 12. Demand response of berth allocations.

Therefore, after the port integrated energy system is fully developed, all kinds of logistic equipment with a management scheme have the potential to become flexible resources of the system, which is the characteristic of "energy-transportation" integration and the difference of port integrated energy system from the land integrated energy system. In this section, some representative logistics activities are presented and modelled. It is noted that these models are exemplary models to characterize the flexibility of the seaport transportation side. The researcher can change these models depending on the operational scenarios and research objectives.

1) Timescales of Different Activities: Table III shows different activities with different time scales. Berth scheduling and intermodal transportation are the links between ports and external transportation systems with the longest time scales. Generally, berth scheduling needs to be scheduled several days to a week ahead, while intermodal transportation needs to be scheduled several weeks to a month ahead. QC scheduling, transferring vehicle scheduling and yard crane scheduling are the main issues of port management, which should be scheduled day ahead. Cold chain scheduling requires precise temperature control, so it should be controlled hourly.

2) Berth Allocation: Berth scheduling is a classic port management problem in which a port system operator allocates berths to ships that berth considering the cold-ironing power, the number of containers to be transferred, the amount of dry bulk cargo/liquid cargo to be loaded and unloaded [84], [85]. The optimal allocation of the berth can balance the berth demand of the seaport. For example, as shown in Fig. 12, when the ship in (time 3, berth 3) is adjusted to serve from (time 1, berth 2), the demand in time 3 can be shifted to time 1. The main constraints of berth scheduling include limits of the total number of berths, berthing duration, draft depth, maximum cold-ironing energy, and the total amount of cargo handling [85]. For ports, the berth scheduling scheme can be adjusted with the above constraints, and then the operation characteristics can be improved from the demand side. Reference [86] proposed a Nash game-based price incentive mechanism of the berth considering the maximum cold-ironing power. The research results show that berth scheduling has great demand-side response potential and can effectively reduce the maximum cold-ironing load in port areas. In the future, the influence of berth scheduling on other port operations of reefer areas, dry bulk cargo, and liquid cargo management is worthy of attention.

The berth scheduling model is presented in the following. The time set of the model is T = 1, 2, ..., t, ..., |T|, with time granularity Δt . Ship set including ships which need to berth is S = 1, 2, ..., s, ..., |S|, and berth set is B = 1, 2, ..., b, ..., |B|. 0 - 1 variable $x_{sbt} = 1$ indicates that the ship s is berthed at the berth b at time t, and $x_sbt = 0$ indicates that it is not berthed.

$$\sum_{t \in T} \sum_{b \in B} x_{sbt} = 1, \forall s \in S$$
(7)

$$\sum_{t \in T} x_{sbt} \le T_{limit.s}, \forall s \in S, b \in B$$
(8)

$$x_{sb(t-1)} - x_{(b(t))} \le 1 - x_{sb\tau}, \forall s \in S, b \in B,$$

$$\tau \in [t+1, \min(t+T_{limit.s} - 1, |T|)]$$
(9)

$$x_{sbt}D_S \le D_b, \forall s \in S, t \in T,$$
(10)

$$x_{sbt}L_S \le L_b, \forall s \in S, t \in T,$$
(11)

$$P_{cold}^{t} = \sum_{b \in B} \sum_{s \in S} x_{sbt} P_{S}, \forall t \in T$$
(12)

$$P_{cargo}^{t} = \sum_{b \in B} \sum_{s \in S} x_{sbt} C_{S}, \forall t \in T$$
(13)

Constraint (7) indicates that any ship can only berth at one berth. Constraint (8) indicates that the ship service time must be greater than $T_{limit.s}$. Constraint (9) ensures that the ship service time is continuous. Constraints (10) and (11) ensure that the berths of the ship have sufficient depth and length. D_S and D_b are the draft depth of ship s and the depth of berth b, respectively. L_S and L_b are the length of the ship s and the berth, respectively. Constraints (12) and (13) are the total cold-ironing power required by the seaport area and the total amount of cargo to be processed, respectively. P_S and C_S are the cold-ironing power required by the ship s and the amount of cargo to be transferred, respectively.

The difficulty of berth scheduling is that x_{sbt} is a threedimensional 0-1 variable. So the problem will be unsolvable due to dimensional disaster when the variable scale expands. The main solution method is to adopt the rule-based method to reduce the space. In the future, the model can be further studied to consider the amount of cargo in a small area of the seaport, and the priority level of the ship.

3) Quay/Yard Cranes: With the high electrification of port equipment, port equipment will become the electrical load. The energy scheduling of port equipment can provide flexibility because the equipment can be operated within a defined period. By



Fig. 13. Power model of seaport cranes.



Fig. 14. Demand response model of seaport cranes.

considering the three steps of lifting, levelling and descending of port equipment operation, reference [19] proposed a trapezoidal model of port equipment power with constant acceleration, as shown in Fig. 13. To better study the seaport equipment model, geometric programming (GP) model of the demand-side response of the seaport engine is established, as shown in Fig. 14. The results for Chongqing Cuntan Port show that the demand-side response of the seaport engine can reduce the operating cost by 12.7%. Since the actual port operation contains multiple activities, future research can adopt a data-driven approach to obtain a more accurate demand-side management model for the seaport from actual operation data.

In Fig. 14, scheme 2 reduces the power (from P_1 to P_2) by extending the operation time (form T_{e1} to T_{e2}). The logistics jobs are both completed by both schemes, that is to say, the corresponding trapezoidal area of scheme 1 and scheme 2 should be the same.

$$\frac{1}{2}P_1(T_{c1} + T_{e1}) = \frac{1}{2}P_2(T_{c2} + T_{e2}) = C_{lift-up}$$
(14)

According to Constraint (14), the demand-side response model of port equipment can be formulated, as shown in Constraint (15)–(17). $i \in I$ represents the *i*-th job that the seaport equipment needs to complete.

$$\frac{1}{2}P_{crane}^{t}(T_{c}^{t}+T_{i}^{t}) = C_{lift-up}, \forall t \in T$$
(15)

 $T_C^t \le T_{C,limit}, \forall t \in T$ (16)

$$\sum_{i \in I} \le T_{cargo}, \forall t \in T$$
(17)



Fig. 15. Operation pattern of belt conveyor.

Where, $T_{c,limit}$ and T_{cargo} are parameters. Constraint (15) is the total job constraint that needs to be satisfied in the demandside response of port equipment. Constraint (16) is the operation constraint of port equipment, that is, the time at the translation state needs to be greater than the lower limit. Constraint (17) is the total time limit for port equipment to complete all jobs. There are bilinear terms in constraint (17), which is the key problem to be solved.

4) Belt Conveyors: The belt conveyors are the main equipment used for transferring dry bulk cargo. Fig. 15 shows the operation pattern of a belt conveyor [86]. In Fig. 15, component c represents the head pulley that drives the belt operation, component b represents the inert pulley that assists the belt system to circulate pulley, component a represents the conveyor belt, and components d and e are counterweight systems to prevent the belt from being stretched rapidly during operation [86].

The energy consumption of belt conveyors has been the focus of research in industrial networks. DIN 22101 standard [87] modelled the energy consumption of belt conveyors which is determined by the combination of the head pulley mass, the belt mass per unit length, the conveyor mass per unit time and the operating speed. Reference [88] proposed a nonlinear model for power calculation of belt conveyors in combination with ISO 5048 and proposed a model parameter estimation method based on least squares and recursive least squares. Reference [73] thus proposed a demand-side response model for the power consumed by belt conveyors. To simplify the complexity of the model, reference [86] studied that when the operating speed does not deviate much from the standard speed, the mass transferred per unit of time can be considered a constant parameter, and the consumed power is approximately a primary function of the operating speed P = kV + b, where k and b are parameters determined by the system structure, and V is the belt transfer system speed. The study set four standard speeds to investigate the power consumption and acceleration/deceleration dynamics around different standard speeds. Thus, the large-scale linear model was replaced by segmented linear models for simplification. The results, based on real-world simulations in the Port of Rotterdam, show that the segmented linear speed adjustment method can save 160 MWh of energy consumption and 90 tons of carbon emissions per year. In the next step, a mixed integer model of the demand response of the belt conveyor was developed with 0 - 1 variables to indicate the operating speed interval. The modelling of the demand-side response of the dry bulk conveyor is shown in constraints (18) and (19). the 0-1

variable o_i^t indicates that the conveyor is operating in the *i*-th operating interval at *t* moments, and the set of operating interval indexes is I = 1, 2, ..., i, ..., |I|.

$$P_{belt}^{t} = \begin{cases} k_{1}v_{belt}^{1,t} + b_{1}, v_{belt}^{1,t} \in V_{1} \\ \cdots \\ k_{i}v_{belt}^{i,t} + b_{i}, v_{belt}^{i,t} \in V_{i} \end{cases}$$
(18)

$$\sum_{t \in T} \sum_{t \in T} o_i^t v_{belt}^{i,t} C_{unit} = C_{belt}$$
(19)

where $k_1, \ldots, k_i, \ldots, k_{|I|}$ and $b_1, \ldots, b_i, \ldots, b_{|I|}$ are parameters of the conveyor in different operating states. $V_1, \ldots, V_i, \ldots, V_{|I|}$ are the corresponding speed intervals. C_{unitis} the total amount of cargo transferred per unit speed (tons/unit speed). C_{belt} is the total number of jobs to be transferred. Under the job constraints, the conveyor can flexibly schedule the consumed power P_{belt}^t , thus realizing the demand-side response of the conveyor.

5) *Reefer Management:* Previous studies on the energy consumption level of cold chain transportation mainly focused on the energy consumption of individual reefer containers. Reference [89] proposed an energy consumption model of a reefer container with parameters including container size and material thermal conductivity. To reduce the energy consumption of the reefer areas, reference [90] proposed an adaptive control method considering the external temperature. The most successful project is the QUEST system proposed by the University of Wageningen in the Netherlands [91], which maintains the internal temperature of containers in a certain range by controlling the ventilation fan rate. With the explosive development of cold chain transportation in 2010–2020, many ports worldwide have large-scale cold chain transportation areas. Communication systems in reference [92], [93], [94] have been commercially applied, which can display the set temperature of containers and the temperature of return air in real-time, which provided a practical basis for centralized power control in the reefer area. In addition, to study the change law of energy consumption in reefer containers and areas, the researcher adopted the computational fluid dynamics simulation method for analysis to explore the relationship between temperature control and container energy consumption [95].

In the port integrated energy system, as the reefer area consumes a large amount of energy, its energy demand model formulation is important. The transfer process of a reefer container from entering the seaport area contains 1) form yard area to reefer area. 2) container stacking area. 3) access to the energy system in the reefer area. 4) Temperature detection and 5) Disconnection from the energy system [38]. Fig. 16 gives the temperature changes of raw fish transported from Iceland to France [38]. Fig. 16 shows the temperature of the reefer container rises rapidly from 0.5 $^{\circ}$ C to 6 $^{\circ}$ C upon arrival at the seaport. In order to characterize the temperature change pattern with or without energy supply, it is necessary to establish the temperature change models of reefer containers in two states, as shown in (20) and



Fig. 16. Temperature changes of cold-chain container.

(21), respectively [38].

1

$$T(t) = T(t-1) + T_A(t-1)e^{AkC_p(1+S)/M}$$
(20)

$$T(t) = T(t-1) + P\Delta t / MC_p \tag{21}$$

$$P_{reefer}(t) = N(t - \Delta t)P \tag{22}$$

where Trepresents the container temperature (C). t represents the time (h). T_A represents the outside temperature (°C). A is the container area (m^2). k represents the thermal insulation constant (W/m^2). represents the sunlight constant. M represents for cargo weight (kg). C_p represents the specific heat capacity of the cargo (kJ/kg). P represents the power (kW). In addition, the following data are needed to complete the modelling of energy consumption in the reefer area of the seaport: 1) The number of reefer containers arriving at the seaport per unit time N(t). 2) The average power delay Δt at the seaport from arrival at the seaport to the reefer area. Constraint (22) defines the consumed energy of the reefer area, where $P_{reefer}(t)$ is the total power consumed in the reefer area.

6) Vehicle Scheduling: To maximize the operation efficiency of the transferring vehicles, seaport system operator needs to solve two main problems: the job assignment problem [96], [97], [98] and the vehicle routing problem [99], [100], [101]. The job assignment problem is to keep the quay and yard cranes in uninterrupted operation while minimizing the idling state of transferring vehicles [96]. The vehicle routing problem is to determine the optimal route for transferring vehicles within the working area [99]. In general, increasing the number of transferring vehicles will improve the transfer efficiency, but it will bring the traffic congestion problem, which leads to the optimal fleet sizing problem [102], [103]. All three problems are difficult to solve as they contain many integer variables. For job assignment problems, rule-based scheduling methods [104], heuristic methods [105] and machine learning methods [106] are usually adopted. For the vehicle routing problem, traditional methods, including the graph search method [107], structural search method [108], artificial potential field method [109], and intelligent algorithm [110] have also been applied. For the optimal vehicle sizing problem, the solution methods include the



Fig. 17. Working flow of seaport vehicle scheduling.

mathematical programming method [102] and the simulationbased method [103].

To reduce the emitted gas emissions from transferring vehicles, transferring vehicles are now gradually moving towards electrification and driving. Electrified transferring vehicles have become the main type of Jurong Port in Singapore [20]. The Port of Los Angeles in the United States has also started to test the operation efficiency of hydrogen-transferring vehicles [111]. Reference [60] on hybrid container trucks shows that hybrid power can reduce energy consumption by 27.1%, and the energy consumed for levelling, lifting and lowering cargo is reduced by 52%, 31% and 11%, respectively. These results will undoubtedly drive the development and application of green transferring vehicles. When electrified and driven transferring vehicles become the dominant type, ports will have to provide sufficient charging power or supply for transferring vehicles. Thus, the three classic types of transferring vehicle dispatching problems are coupled with the operation of the seaport's integrated energy system. In other words, while completing the cargo transfer job in the seaport, the seaport needs to develop an energy management plan in advance to provide an energy supply for the transferring vehicles. Reference [18] investigates this problem using a multi-agent system and shows that the charging and discharging of the transferring vehicles can provide additional flexibility to the seaport operation.

This section proposes a class of exemplary models for vehicle scheduling from an energy scheduling perspective, and other ideas can be modelled accordingly by drawing on current research results. The study time length of the model is T = 1, 2, ..., t, ..., |T|. The unit time length is Δt . The set of port vehicles is I = 1, 2, ..., i, ..., |I|. The set of paths is J = 1, 2, ..., j, ..., |J|. For modelling purposes, this section assumes that any port vehicle has three operating states: transfer $(o_{i,w}^t = 1)$, charging $(o_{i,c}^t = 1)$ and servicing $(o_{i,r}^t = 1)$. And it lasts for a period in any operating state. Scenarios 1-3 in Fig. 17 are typical examples where the transit, charging and overhaul times are defined as $T_{i,w}, T_{i,c}, T_{i,r}$. For path selection, $t_{ij}^t = 1$ represents the selection of the *i*-th vehicle to select the *j*-th transit route at *t* moment.

The above are common assumptions for transportation-side modelling, while the modelling of the energy side, i.e., the correspondence between the job completion time and the consumed power, is the key to completing the modelling of the demand-side response, and the current research lacks a modelling method for this part, which is assumed in this section as (25), where C^t is the ratio of the number of jobs completed at t moments compared to the standard amount, P^t is the consumed power, θ is the system parameter, f is the given functional relationship, which can be obtained by theoretical analysis or data-driven methods, and can be assumed as a linear relationship $C^t = f(P^t, \theta)$ for simplicity of modelling.

$$o_{i,w}^{t} + o_{i,c}^{t} + o_{i,r}^{t} = 1, \forall i \in I, t \in T$$
 (23)

$$T_{i,w} + T_{i,c}T_{i,r} = |T|, \forall i \in I$$
(24)

$$\begin{cases}
o_{i,\zeta}^{t-1} - o_{i,\zeta}^{t} \leq 1 - o_{i,\zeta}^{\tau}, \forall i \in I, t \in T \setminus 1 \\
\tau \in [t+1, \min(t+T_{i,\zeta}-1, |T|)] \\
\zeta = (w, c, r) \\
\sum_{t \in T} \sum_{i \in I} o_{i,w}^{t} C_{w}^{t} V_{i} = V_{w}
\end{cases}$$
(25)

$$\sum_{j=J} r_{ij}^t = 1, \forall i \in I, t \in T$$
(26)

$$\begin{cases} r_{ij}^{t-1} - r_{ij}^t \le 1 - r_{ij}^{\tau}, \forall i \in I, j \in J, t \in T \setminus 1 \\ \tau \in [t+1, \min(t+T_{i,w}-1, |T|)] \end{cases}$$
(27)

$$\sum_{i=I} o_{i,w}^t t_{ij}^t \le G_j, \forall j \in J, t \in T$$
(28)

$$\sum_{t \in T} o_{i,w}^t P_{i,w}^t = \sum_{t \in T} o_{i,c}^t P_{i,c}^t, \forall i \in I$$

$$(29)$$

$$P_S^t = \sum_{i \in I} o_{i,c}^t P_{i,c}^t, \forall t \in T$$
(30)

Constraints (23)–(27) are the job constraints. Where C_w^t represents the ratio of the actually completed job volume of the transferring vehicle compared to the standard volume, which satisfies the constraint of Constraint (23) with the consumed power. V_i and V_w represent the standard job volume and the total logistics job volume of the ith vehicle in unit time, respectively. Constraint (24) represents that any vehicle can only be in one working state at any moment. Constraint (25) represents that the sum of the three working state times is equal to the total length of the running time cycle. Constraint (26) is to ensure that any work cycle time is continuous. Constraint (27) is the total logistics job constraint. Constraints (28)-(30) are the path selection constraints of the vehicle. Where G_i represents the capacity of the jth route. Constraint (28) represents that any vehicle can only choose one path at any time. Constraint (29) represents that after choosing a path, it occupies a certain of working time this route. Constraint (30) represents that any route needs to accommodate vehicles within the upper limit. Constraints (31)–(32) are the energy constraints of the vehicle. P_s^t is the total power consumed by all transferring vehicles in the seaport area for charging. Constraint (31) indicates that the energy consumed by any vehicle in the study cycle needs to be balanced with the charging energy. Constraint (32) is the total charging power in the seaport area. From the above model, it can be seen that the flexibility of the vehicle scheduling model comes from the C_W^t in Constraint (27), while different C_W^t



Fig. 18. Railway station in Beilun port.

corresponds to different consumed power $P_{i,w}^t$, which in turn couples the energy side of the seaport area through Constraint (31) and helps the optimal operation of the port integrated energy system together with the flexibility provided by the charging power $P_{i,c}^t$. The flexibility on the transportation side represented by $P_{i,w}^t$ and the flexibility on the energy side represented by $P_{i,c}^t$ is also a symbolic representation of the "transportation-energy" coupling in the seaport.

Mathematically, the seaport vehicle dispatch energy model defined by Constraints (23)–(32) has a two-layer structure, because Constraints (26), (29) are unknown in the cases of $T_{i,w}, T_{i,c}, T_{i,r}$, which makes the model difficult to solve by classical algorithms. In practice, given $T_{i,w}, T_{i,c}, T_{i,r}$, a hierarchical solution idea can be used to approximate the problem.

7) Intermodal Transportation: The port is the connection between water and land transportation, and after the cargo is processed in the seaport area, it needs to be connected to the land transportation system for the next stage of transportation, which usually includes rail and road transportation. Generally speaking, the capacity of water transport is closer to that of rail transport, and the cooperation between the two can greatly improve logistics efficiency. Currently, the rate of water-rail intermodal transport of cargo in major ports in the world is higher than 30% [112]. Due to the rapid development of Chinese ports, the speed of railroad construction is slower than the speed of port expansion, so the ratio of water-rail intermodal transport is lower than the international level, and some ports are lower than 20% [112], while the rate of railroad access to ports in China is low, and the "last mile" transportation job between ports and railroads has long relied on road transport, with small capacity and easy to block. The small capacity and easy blockage greatly restrict the transportation system's efficiency. Therefore, the rail access plan for major ports was an important development project in China during the 14th Five-Year Plan. Fig. 18 shows the Beilun railroad port layout in China [112]. In Fig. 18, the red area represents the incoming railroad, and the intermodal port needs to complete the cargo transfer between the seaport yard (yellow area) and the railroad yard (green area). The transfer between yards is

mainly carried out by transferring vehicles. At the same time, the operation of water-rail intermodal transport is also influenced by constraints such as the departure time of the seaport railroad and the cargo volume [112]. Therefore, the water-rail intermodal transport can be considered a vehicle scheduling problem with the departure time as the time constraint and the cargo volume as the upper limit constraint.

$$|T| \le T_{railway} \tag{31}$$

$$V_w \le V_{railway} \tag{32}$$

where $T_{railway}$ and $V_{railway}$ represent the railroad dispatching time and the total amount of railroad freight, respectively. Constraint (31) represents that the vehicle dispatching time is less than the railroad dispatching cycle. Constraint (32) represents that the total amount of freight is less than the railroad capacity. Since constraints (31) and (32) are both aggregate constraints, water-rail intermodal transport can provide operational flexibility for the port integrated energy system.

C. Models of Integrated Energy Storage

1) Physical Energy Storage: The physical energy storage system consists of traditional electric and thermal energy storage to keep the power on and prevent energy shortages. In general, energy storage is expected to charge at low-price and recharge at high-price periods. Electric and thermal energy storages with high energy efficiency are common in energy systems. However, electric energy storage has a high installation cost and a short health life cycle. Thermal energy storage, which stores excess energy and then releases it when the heat load is high, is relatively inexpensive compared to electric energy storage.

$$\begin{cases} ES_{t+1} = ES_t + \eta_c P_t^{char} - \eta_d P_t^{dischar}, \forall t \in T \\ ES_{\min} \leq ES_t \leq ES_{\max}, \forall t \in T \\ ES_0 = ES_T \\ Z_t^{char}, Z_t^{dischar} \in \{0, 1\}, \forall t \in T \\ 0 \leq P_t^{char} + Z_t^{dischar} \leq 1, \forall t \in T \\ 0 \leq P_t^{char} \leq Z_t^{char} P_{\max}^{char}, \forall t \in T \\ 0 \leq P_t^{dischar} \leq Z_t^{dischar} P_{\max}^{dischar}, \forall t \in T \\ \end{bmatrix} \begin{cases} HS_{t+1} = HS_t + \eta_i nH_t^{in} - \eta_{out} H_t^{out}, \forall t \in T \\ HS_{0} = HS_T \\ Y_t^{in}, Y_t^{out} \in \{0, 1\}, \forall t \in T \\ Q \leq H_t^{in} \leq Y_t^{in} H_{\max}^{in}, \forall t \in T \end{cases}$$
(34)

The electric energy storage model is described by (33). It should be noted that the electric energy storage model uses a binary variable Z_t to indicate whether the electric energy storage is charged or discharged, thus linearizing the constraint [113], [114]. Similar to electric energy storage, the formulas for thermal energy storage are given in (34).



Fig. 19. Storage tank for evaporating liquid.

2) Virtual Energy Storage: Acting as power/energy buffers, energy storage devices have always been associated with energy systems to improve the operational flexibility and have been widely studied in power system applications [115], [116], [117]. In integrated energy systems, various types of gas and heat storage equipment can also smooth out differences in the distribution of various loads and improve the overall economic efficiency of the system [118], [119]. In addition, the actual operation also includes a type of "broad energy storage" that consists of a combination of P2G devices and fuel cells. P2G devices "absorb energy", and fuel cells "emit energy", and this combination of devices has gained increasing attention in the shipping industry [120].

Regarding thermal storage, reference [121] uses the thermal model of energy storage with a cold water layer/hot water layer to build an energy management model for cruise ships with large capacity cold/heat loads to improve the operational flexibility of ships. Reference [122] proposed a long-timescale gas storage operation method considering the impact of gas prices.

In integrated energy systems in ports, multiple energy flows bring a wider range of energy storage needs. In addition to the traditional electrical and thermal energy storage, the fuel storage system of the port integrated energy system can be considered a special type of energy storage system. In Fig. 19, liquid fuel is stored in the fuel tank by liquid pumps, and the gravitational potential energy from the difference between the high and low heads of the fuel tank has the potential for energy storage. Reference [123] investigates this problem and shows that the head difference in the liquid tank can be combined with thermal energy storage to improve the system's economics. Reference [82] investigates the coordinated operation of liquid hydrogen storage tanks with electric power systems as an example. It is also worth noting that the main fuel types are highly volatile and therefore need to be stored in a specific pressure and temperature range, and this flexible range has the potential to provide "energy storage" for the system.

This section presents a mathematical model of this type of storage device, Fig. 19 gives the structure of a liquid hydrogen storage tank containing "gas-liquid" coupling, and the mathematical model is given in Constraints (35)–(39). The length of

study time for the following model is T, and the unit time length is t.

$$V_l^{t+1} = V_l^t + (q_{in}^t + q_{g2l}^t)\Delta t - q_{out}^t\Delta t - k_v V_l^t,$$

$$\forall t \in T \setminus \{\max(T)\}$$
(35)

$$\frac{P_g^{t+1}V_g^{t+1}}{RT} + k_n^t V_v^t V_l^t - \frac{P_g^t(q_g^t \Delta t)}{RT},$$

$$\forall t \in T \setminus \{\max(T)\}$$
(36)

$$V_{t}^{t} + V_{t}^{t} = V, \quad \forall t \in T$$

$$(37)$$

$$\begin{cases} q_{g2l} - \kappa_{com} q_g \\ P_{com}^t = k_{power} q_g^t \Delta t, \forall t \in T \end{cases}$$

$$(38)$$

$$\begin{cases}
P_{\min} \leq P_g^t \leq P_{\max} \\
V_l^t \geq 0, V_g^t \geq 0 \\
q_{in}^{\max} \leq q_{in}^t \leq q_{inn}^{\max} \\
q_{out}^{\max} \leq q_{out}^t \leq q_{out}^{\max} \\
q_{gal}^{\max} \leq q_g^t \leq q_g^{\max} \\
q_{g2l}^{\max} \leq q_{g2l}^t \leq q_{g2l}^{\max}
\end{cases}$$
(39)

Constraint (35) is the liquid-phase material balance constraint. In the liquid hydrogen storage tank, the liquid-phase equilibrium consists of three liquid streams: inflow liquid stream, outflow liquid stream and evaporation, where the evaporation is proportional to the current liquid volume [82] and k_v represents the evaporation constant, which is taken as 0.2% (dimensionless) in reference [82], i.e., 0.2% of liquid hydrogen is converted to the gaseous state every hour. Constraint (36) is the gas-phase material equilibrium constraint. In a liquid hydrogen storage tank, the gas-phase equilibrium consists of two fluid components: the evaporative replenishment and the amount of re-liquefied material. Since the gas volume varies with the gas pressure, the gas-phase equilibrium is based on the amount of substance, and the gas satisfies the gas constraint PV = enRT, P and V are the air pressure (pal) and volume (m^3) , respectively, and n is the amount of substance (moles, mol), R is the standard gas constant, and T is the Kelvin temperature (Kelvin, K). In evaporation supplementation, k_n is the amount of liquid substance per unit volume (mol/m^3) . Constraint (37) is the storage volume constraint. This constraint means that both the liquid and the gas are confined in a closed storage tank, where it is assumed that the storage tank is well sealed. In general, the daily consumption of the currently used seamless steel storage tanks is negligible, so V_s is a constant. Constraint (38) is the compressor constraint. In this constraint, k_{com} is the gas-liquid compression ratio (dimensionless), k_{power} is the power consumed per unit volume of gas compressed into liquid (kW/m^3) , and P_{com}^t represents the power consumed by the compressor at time t(kW). Constraint (39) constrains the upper and lower bounds of the state variables. This constraint is an upper and lower bound on the variables involved in the model, including the air pressure inside the storage tank, the volume of the liquid and gas phases, and the flow rate of each gas and a liquid stream.

ModelExisting challengesAvailable solutionsShortcomings of solutionsMultiple energy flow coordinationBoth the gas and liquid phase constraints are nonlinear [81].Linearization can be used to transform nonlinear constraints [82]. The transmission speed of "gas" is faster than that of "liquid", so the time constant is shorter [80].Linearization can be used to transform nonlinear constraints [82]. The rule-based method can be adopted to solve problems with large-scale solution spaces [124].The solution accuracy using linearization and convexification can be used to tansform holds are heteroary using linearization and convexification can be used to tansform holds are heteroary using linearization and convexification can be used to tansform holds are heteroary using linearization and convexification can be used to tansform holds are heteroary using linearization and convexification can be used to tansform holds are heteroary using linearization and convexification can be used to tansform holinear constraints into linear constraints into linear constraints into linear constraints [21].The stability and scalability of reinforcement learning can a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [82].Belt conveyorsThere are many binary variables in constraints [31].There are many binary variables [124].The stability and scalability of reinforcement learning can al onconvex [32].The stability and scalability of reinforcement learning can also be dopted to solve the problem with variables [124].The stability and scalability of reinforcement learning can also be adopted to solve the problem				
Multiple energy flow coordinationBoth the gas and liquid phase constraints are nonlinear [81].Internzation can be used to transform nonlinear constraints [82].The solution accuracy using transform constraints [82].Berth allocation x_{abc} is a three-dimensional binary variable [83], [84]. So the problem wirable [83], [84]. So the problem wirable scale expands.The rule-based method can be adopted to reduce the space. Reinforcement learning can also be adopted to solve problems with large-scale solution space localability of reinforcement learning can be used to ransform bilinear variables [124].For different port environments, rule-based methods are heterogeneous. The stability and calability of reinforcement learning can be used to ransform bilinear variables [124].For different port environments, rule-based methods are heterogeneous. The solution accuracy using incarization and convextification can be used to ransform bilinear variables [124].For different port environment, rule-based methods are heterogeneous. The solution accuracy using incarization and convextification refer containers are nonlinear and noncovex [39].For different port environment, rule-based method scale builty of reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].For different port environment, rule-based method, scale problem to be considered [9].Welkicle schedulingThere are many binary variables in constraints (18)-10), resulting in low solving efficiency [88].Reinforcement learning can al noncovex (182].Reinforcement learning can be used to solve the problem with ta large number of binary variables [82].T	Model	Existing challenges	Available solutions	Shortcomings of solutions
Number energy flow coordinationconstraints are nonlinear [81]. The transmission speed of "gas" is faster than that of "liquid", so the me constraints is shorter [80].mean constraints [82]. The intervals, considered [82].mean constraints and considered [82].Berth allocation x_{edd} is a three-dimensional binary variable scale expands.The rule-based method can be adopted to reduce the space. Reinforcement learning can also be adopted to solve problems with large-scale solution spaces [124].The solution space becomes larger, resulting in poor solution efficiency [108].Quay/yard cranesThere are bilinear terms in constraint (17) [19].There are many binary variables [124].There are many binary variables [82].For different port ensolution spaces [124].Belt conveyorsThere are many binary variables in constraints (18)-(19), resulting in low solving efficiency [88].Reinforcement learning can and nonconvex [39].Reinforcement learning can aloo to transform incear constraints [82].The solution accuracy using incear constraints [82].Nehicle dispatch energy storageThere are many binary variables (12)-(30) has a two-layer storageReinforcement learning can also be adopted to solve problems with alarge number of binary variables [124].The solution accuracy using incear constraints [82].Physical energy storageThere are many binary variables in constraint (30) (112).The sale alberg models can be used to transform transform in new solving efficiency [18].The care constraints (82].Physical energy storageThere are many binary variables in low solving efficiency [18]. </td <td>M. 1(1) 1.</td> <td>Both the gas and liquid phase</td> <td>Linearization can be used to</td> <td>The solution accuracy using</td>	M. 1(1) 1.	Both the gas and liquid phase	Linearization can be used to	The solution accuracy using
now coordinationThe transmission speed of "gas" is faster than that of "liquid", so the time constant is shorter [80].Considered [82].Considered [82].Berth allocation x_{abt} is a three-dimensional binary variable [83]. [84]. So the problem the unsolvable due to dimensional disaster when the variable scale expands.The rule-based method can be adopted to roduce the space. Reinforcement learning can also be adopted to solve problems with large-scale solution spaces [124].The solution space becomes activity and calability of reinforcement learning can adopted to roduce the space. The stability and calability of reinforcement learning can adopted to solve problems with a large number of binary variables [82].There are many binary variables [82].There are many binary variables [82].There are many binary variables [82].Reinforcement learning can adopted to solve problems with a large number of binary variables [82].The solution accuracy using incerization and convexification read to solve problems with a large number of binary variables [82].The solution accuracy using incerization and convexification read to stackelerg models can be used with is characteristion magent-environment, interactor [124].It is hard to find the equilibrium considered [9].Physical energy storageThere are many binary variables in low solving efficiency [18].There are many binary variables in low solving efficiency [18].The reasformed before to solve abolite value functions reinforcement learning can also be adopted to roducan before to solve a	Multiple energy	constraints are nonlinear [81].	into lincon constraints	inearization need to be
IntermediationThe transmission speed of "gas" is faster than that of "liquid", so the time constant is shorter [80].The mine of a bidded into smaller intervals, constraint is shorter [80].The solution space becomes larger, resulting in poor scheduling.Berth allocation x_{abt} is a three-dimensional binary wariable [83], [84]. So the problem will be unsolvable due to trainable scale expands.The solution space becomes larger, resulting in poor scheduling.For different port environments, rule-based methods are heterogeneous. The stability and calability or environments, rule-based methods are heterogeneous. The stability and calability or environment increased to solve problems with a large number of binary variables [124]. Linearization and convexification can be used to stackelberg models can be used to solve problem with worlabels [124].The solution accuracy using linearization and convexification can be used to stackelberg models can be used to stackelberg models can be used to stackelberg models. The stackelberg models can be used to stackelberg models. The stackelberg models can be used to stackelberg models can be used to stackelberg models. The zero-segmentation method, gase_tervironment interacteristion 124].The solution accuracy using linearization and convexification can be	now coordination		Time interrel of "liquid"	considered [82].
Intermedial is faster than the of "liquid", so the time constant is shorter [80].Intermals, and of the time constant is shorter [80].Intermals, and of the time constant is shorter [80].Berth allocation x_{sht} is a three-dimensional binary witable [83], [44]. So the problem will be unsolvable due to dimensional disaster when the variable scale expands.The rule-based method can be adopted to solve problems with large-scale solution spaces [124].For different port environments, rule-based methods are heterogeneous. The stability and calability of reinforcement learning can be used to transform bilinear tarbales [82].For different port environments, rule-based methods are heterogeneous. The stability and calability of reinforcement learning can be used to solve problems with large-scale solution spaces [124].Quay/yard cranesThere are many binary variables [82].Reinforcement learning can be adopted to solve problems with a large number of binary variables [82].For different port environment incariants into linearization and convexification can be used to solve problems with a large number of binary variables [82].Belt conveyorsThere are many binary visible [82].Reinforcement learning can be adopted to solve problems with a large number of binary variables [82].The stability and scalability of reinforcement learning can adononovex [39].Intermodal transportationThere are absolute value functions in constraints (31) (112].There are many binary variables to be vosive absolute cale product on solve absolute cale of solve problems with all arge number of binary variables [124].The transformed bind of reinforcemen		The transmission speed of "gas"	scheduling can be divided	The solution space becomes
Berth allocation x_{abt} is a three-dimensional binary variable [83], [84]. So the problem will be unsolvable due to dimensional disaster when the variable scale expands.Intermediation and convexification also be adopted to solve problems with large-scale solution spaces [124].For different port environments, rule-based methods are heterogeneous. The solution accuracy using linearization and convexification and nonconvex [39].For different port environments, rule-based methods are heterogeneous. The solution spaces [124].Belt conveyorsThere are many binary variables [124].Linearization and convexification can be used to transform bilinear constraints (18)-(19), resulting in low solving efficiency [88].Reinforcement learning can be used to transform bilinear constraints [82].For different port environments, rule-based methods are heterogeneous. The solution accuracy using linearization and convexification a large number of binary variables [22].For different port environments, rule-based methods are heterogeneous. The solution accuracy using linearization and convexification a large number of binary variables [22].For different port environment intervalues [24].Belt conveyorsThere are many binary variables [22].Reinforcement learning can a large number of binary variables [24].The solution accuracy using linearization and convexification nonlinear constraints [82].Nuthered is port of the solution accuracy using linearization and nonconvex [39].The solution accuracy using linearization and convexification nonlinear constraints [82].Physical energy storageThere are many binary variables in constraints (33)-(34), resulting		is faster than that of "liquid" so	into smaller intervals	larger resulting in poor
Berth allocation x_{sbc} is a three-dimensional binary variables [84]. (4.) So the problem will be unsolvable due to dimensional disaster when the variables cale expands.Scheduling. The tradopted to reduce the space. Reinforcement learning can be adopted to solve problems with large-scale solution spaces [124].For different port environments, rule-based methods are heterogeneous. The stability and calability of reinforcement learning needs to be considered [9]. The solution accuracy using linearization and convexification can be used to transform binary variables in constraints olving efficiency [88].Reinforcement learning can be adopted to orly problems with a large number of binary variables [82].There are many binary variables in constraints adopted to solve problems with a large number of binary variables [82].The stability and scalability of reinforcement learning needs to be considered [9].Belt conveyorsThere are many binary variables in constraints (18)-(19), resulting in low solving efficiency [89].Reinforcement learning can be adopted to solve problems with a large number of binary variables [82].The stability and scalability of reinforcement learning needs to be considered [9].Wehicle schedulingMathematically, the seaport vheile dispatch energy model (23)-(30) has a two-layer storageReinforcement learning can also be used with its characteristic on agent-environment interaction [124].The solution accuracy using incaristity and calability of reinforcement learning needs to be considered [8].Physical energy storageThere are many binary variables in constraints (33)-(34), resulting in constraints (33)-(34), resulting s		the time constant is shorter [80].	consistent with "gas"	solution efficiency [106].
Berth allocation x_{sbt} is a three-dimensional binary variable [83], [84]. So the problem will be unsolvable due to dimensional disaster when the variable scale expands.The rule-based method can be adopted to roluce the space. Reinforcement learning can also be adopted to solve problems with large-scale abso be adopted to solve problems with a large number of reinforcement learning needs to be considered [9]. The stability and calability of reinforcement learning needs to be considered [82].For different port environments, rule-based methods are heterogeneous. The stability and calability of reinforcement learning needs to be considered [82].Quay/yard cranesThere are bilinear terms in constraint (17) [19].Linearization and convexification a large number of binary variables [82].The stability and calability of reinforcement learning needs to be considered [82].Belt conveyorsThere are many binary variables file (18). (19), resulting in low solving efficiency [88].Reinforcement learning can ba a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [9].Vehicle schedulingMathematically, the seaport vehicle dispatch energy model defined by constraints (23). (30) has a two-layer storageReinforcement learning can also be used to solve the problem with two-layer structure. Furthermore, reinforcement learning can also be adopted to solve two-layer structure. Furthermore, referer containts (31)The sate absolute value functions in constraint (31)Physical energy storageThere are many binary variables functions in constraint (31)There are many binary variables solve aboliu		[].	scheduling.	
Berth allocationJeak Bis a furge-entimisional pinationbe adopted to reduce the space. also be adopted to solve problems with large-scale also be adopted to solve problems with large-scale and convexification can be used to transform bilinear terms into linear constraints with the help of auxiliary variables in constraints (18)-(19), resulting in low solving efficiency [88].Linearization and convexification can be used to solve problems with adopted to solve problem suitary variables, solving efficiency [88].These set on solve adopted is solve problem with adopted to solve problem with adopted to solve problem with two-layer structure. Furthermore, reforcement learning can laso be used to transform bilinear can be used to transform bilinearization and convexification can be used to trans			The rule-based method can	For different port
Berth allocationVariable [30], [30], iso the problem dimensional disaster when the variable scale expands.Reinforcement learning can also be adpleted to solve problems with large-scale solution spaces [124].methods are heterogeneous. methods are heterogeneous.Quay/yard cranesThere are bilinear terms in constraint (17) [19].Linearization and convexification can be used to transform bilinear terms into linear constraints with the help of auxiliary variables [82].methods are heterogeneous. methods are heterogeneous.Belt conveyorsThere are many binary variables in constraints (18)-(19), resulting in low solving efficiency [88].Reinforcement learning can adopted to solve problems with a large number of binary variables [82].Reinforcement learning can adopted to solve problems with a large number of binary variables [82].The solution accuracy using linearization and convexification can be used to transform nonlinear constraints linto incer constraints linto linearization and convexification can be used to transform onlinear constraints linto linearization and convexification can be used to solve the problem with a large number of binary variables [24].The solution accuracy using linearization and convexification can be used to transform nonlinear constraints linto linearization and convexification can be used to transform linearization and convexification nonlinear constraints linto linearization and convexification nonlinear constraints linto linearization and convexification can be used to solve the problem with subary variables [24].The solution accuracy using linearization and convexification nonlinear constraints linto linearization and convexification nonlinear cons		x_{sbt} is a three-dimensional binary	be adopted to reduce the space.	environments, rule-based
Definit and canonwill be mask-harden used to the tody wariable scale expands.The end the terms in constraint (17) [19].also be adopted to solve problems with large-scale solution spaces [124].The estability and calability of reinforcement learning needs to be considered [9].Quay/yard cranesThere are bilinear terms in constraint (17) [19].Linearization and convexification can be used to transform bilinear veriables in constraints solving efficiency [88].Linearization and convexification can be used to transform bilinear can be used to transform bilinear variables [82].The stability and calability of reinforcement learning needs to be considered [9].Reefer managementTemperature charge models of reefer containers are nonlinear and nonconvex [39].Reinforcement learning needs to be considered can be used to transform nonlinear constraints [82].The solution accuracy using linearization and convexification need to be considered [9].Vehicle schedulingMathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].There are absolute value functions in constraint (31) [112].The rare absolute value functions in constraint (31) [112].There are absolute value functions in constraint (33)-(34), resenting in low solving efficiency [118].The rare function accuracy using linearization and convexification needs to be transformed before it can be used with a large number of binary variables [124].The transformed model is a non-convex nonlinear model, square method, geometric meaning method can be used to solve absolute value functions. Reinforcement learning reads to be considered [9]. <td< td=""><td>Borth allocation</td><td>will be unsolvable due to</td><td>Reinforcement learning can</td><td>methods are heterogeneous.</td></td<>	Borth allocation	will be unsolvable due to	Reinforcement learning can	methods are heterogeneous.
Quay/yard cranesThere are bilinear terms in constraint (17) [19].problems with large-scale solution spaces [124].of reinforcement learning incarization and convexification can be used to transform bilinear with the help of auxiliary variables [82].of reinforcement learning incarization and convexification need to be considered [9].Belt conveyorsThere are many binary variables in constraints (18)-(19), resulting in low solving efficiency [38].Reinforcement learning can adopted to solve problems with a large number of binary variables [22].The solution accuracy using linearization and convexification refer containers are nonlinear and nonconvex [39].Reefer managementTemperature change models of reefer containers are nonlinear and nonconvex [39].Reinforcement learning can adopted to solve problems with a large number of binary variables [22].The solution accuracy using linearization and convexification need to be considered [82].Vehicle schedulingMathematically, the seaport which delipatch energy (23)-(30) has a two-layer storageMathematically, the seaport functions in constraints (31) (112].Reinforcement learning can also be adopted to solve the problem with a large number of binary storageI's hard to find the equilibrium point of Bilevel or Stackelberg models. The transformed model is a non-convex nonlinear model, square method, geometric meaning method can bused to bolve directly to solve absolute value functions. Reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The stability of reinforcement learning can also be adopted to solve problems with a large number of binary	Dertif allocation	dimensional disaster when the	also be adopted to solve	The stability and calability
Quay/yard cranesThere are bilinear terms in constraint (17) [19].solution spaces [124].needs to be considered [9].Quay/yard cranesThere are bilinear terms in constraint (17) [19].Linearization and convexification raniables [82].needs to be considered [82]. With more auxiliary variables, solving efficiency is also a problem to be considered [9].Belt conveyorsThere are many binary variables in constraints (18)-(19), resulting in low solving efficiency [88].Reinforcement learning can be adopted to solve problems with a large number of binary variables [124].The solution accuracy using linearization and convexification can be used to transform nonlinear constraints into linear constraints into linearization and convexification can be used to solve the problem with two-layer structure. Furthermore, reinforcement learning can be used to tassform monlinear and nonconvex [39].The are absolute value functions in constraints (31) (112].There are absolute value functions in constraint (31) (112].There are absolute value functions in constraint (31) (112].There are many binary variables in low solving efficiency [118].The transformed before also be adopted to solve problems with a large number on solve absolute value functions. Reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The transformed before reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The transformed before reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The transformed before reinforcement learning can also		variable scale expands	problems with large-scale	of reinforcement learning
Quay/yard cranesThere are bilinear terms in constraint (17) [19].Linearization and convexification can be used to transform bilinear terms into linear constraints with the help of auxiliary variables [82].The solution accuracy using linearization and convexification need to be considered [82]. With more auxiliary variables, solving efficiency [88].Belt conveyorsThere are many binary variables in constraints (18)-(19), resulting in low solving efficiency [88].Reinforcement learning can be adopted to solve problems with a large number of binary variables [124].The solution accuracy using linearization and convexification reade to be considered [9].Reefer managementTemperature change models of refer containers are nonlinear and noconvex [39].Reinforcement learning can be adopted to solve problems with a large number of binary variables [124].The solution accuracy using linearization and convexification needs to be considered [8].Vehicle schedulingMathematically, the seaport vehicle dispatch energy model (23)-(30) has a two-layer structure [11].Stackelberg models can be used to solve the problem with reinforcement learning can also be used to solve the problem with (124].It's hard to find the equilibrium models. The stability and scalability of reinforcement learning needs to be considered [9].Physical energy storageThere are many binary variables in low solving efficiency [118].The zero-segmentation meaning method can be used to solve absolute value functions. Reinforcement learning needs to solve absolute value functions, neaning method can be used to transform binary variables [24].The transform dole is a non-convex			solution spaces [124].	needs to be considered [9].
Quay/yard cranesThere are bilinear terms in constraint (17) [19].can be used to transform bilinear terms into linear constraints with the help of auxiliary variables [82].Interavation and convexitation meed to be considered [82]. With more auxiliary variables, solving efficiency is also a problem to be considered.Belt conveyorsThere are many binary variables in constraints (18)-(19), resulting in low solving efficiency [88].Reinforcement learning can be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [82].Reefer managementMathematically, the seaport vehicle dispatch energy (23)-(30) has a two-layer storageReinforcement learning can add nonconvex [39].Reinforcement learning can be used to transform nonlinear constraints [82]. Bilevel or Stackelberg models can be used to solve the problem with two-layer structure. Furthermore, reinforcement learning can also be used with its characteristic on agent-environment interaction [124].The reasbolity and scalability of reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].It's hard to find the equilibrium point of Bilevel or Stackelberg models can be used with its characteristic on agent-environment interaction [124].It's hard to find the equilibrium point of Bilevel or Stackelberg models. The stability and scalability of reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].It's hard to find the equilibrium point of Bilevel or Stackelberg models can be used with its characteristic on agent-environment <b< td=""><td></td><td></td><td>Linearization and convexification</td><td>The solution accuracy using</td></b<>			Linearization and convexification	The solution accuracy using
Quay/yard cranesInter are binnear terms into constraint (17) [19].terms into linear constraints with the help of auxiliary variables [82].terms into linear constraints with the help of auxiliary variables [82].more auxiliary variables, solving efficiency is also a problem to be considered [9].Belt conveyorsThere are many binary variables in constraints (18)-(19), resulting in low solving efficiency [88].Reinforcement learning can a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [9].Wehicle schedulingMathematically, the scaport vehicle lispatch energy storageMathematically, the scaport twoild bigatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Reinforcement a large number of binary variables [82].It's hard to find the equilibrium point of Bilevel or Stackelberg models. The stability and scalability of reinforcement learning can also can be used to solve the problem with two-layer structure. Furthermore, reinforcement learning can also be used with its characteristic on agent-environment in low solving efficiency [118].It's hard to find the equilibrium point of Bilevel or Stackelberg models. The stability of reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].It's hard to find the equilibrium point of Bilevel or Stackelberg models. The stability of reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].Physical energy storageThere are many binary variables in low solving efficiency [118].Gas-phase equilibrium constraint		There are hilinean terms in	can be used to transform bilinear	need to be considered [92] With
Belt conveyorsThere are many binary variables in constraints (18)-(19), resulting in low solving efficiency [88].Reinforcement learning can be adopted to solve problems with a large number of binary variables [124].Reinforcement learning can be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [9].Wehicle schedulingMathematically, the seaport vehicle dispatch energy structure [11].Mathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Mathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Mathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Mathematically, the seaport vehicle dispatch energy model defined by constraints (33)-(34), resulting in low solving efficiency [118].Mathematically, the seaport vehicle dispatch energy model defined by constraints (31) [112].Mathematically, the seaport vehicle dispatch energy model defined by constraints (31)-(34), resulting in low solving efficiency [118].The zear absolute value functions in constraint (31) [112].The zear absolute value functions in constraint (31) [112].The zear absolute value fo inary variables in constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].The zear absolute value functions in constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].The seatility and sc	Quay/yard cranes	constraint (17) [19]	terms into linear constraints	more auxiliary variables solving
Variables [82].Control for the considered.Belt conveyorsThere are many binary variables in constraints (18)-(19), resulting in low solving efficiency [88].Reinforcement learning can be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [9].Reefer managementTemperature change models of reefer containers are nonlinear and nonconvex [39].Reinforcement learning can be adopted to solve problems with a large number of binary variables [82].The solution accuracy using linear constraints into linear constraints [82].Vehicle schedulingMathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Bilevel or Stackelberg models can be used to solve the problem with two-layer structure. Furthermore, reinforcement learning can also be used with its characteristic on agent-environment interaction [124].It's hard to find the equilibrium point of Bilevel or Stackelberg models. The stability and scalability of reinforcement learning needs to be considered [9].Intermodal transportationThere are absolute value functions in constraint (31) in low solving efficiency [118].The reare many binary variables in low solving efficiency [118].The stability and scalability of reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].Virtual energy storageGas-phase equilibrium constraint		constraint (17) [13].	with the help of auxiliary	efficiency is also a problem
Belt conveyorsThere are many binary variables in constraints (18)-(19), resulting in low solving efficiency [88].Reinforcement learning can be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [9].Reefer managementTemperature change models of reefer containers are nonlinear and nonconvex [39].Temperature change models of reefer containers are nonlinear and nonconvex [39].Linearization and convexification can be used to transform nonlinear constraints into linear constraints [82].The solution accuracy using linearization and convexification can be used to straintsVehicle schedulingMathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Mathematically, the seaport vehicle dispatch energy model defined by constraints (31) [112].There are absolute value functions in constraint (31) [112].There are absolute value functions in constraint (31) [112].There are many binary variables in constraint (31), [31].The reare many binary variables in low solving efficiency [118].The adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [9].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].The help of auxilizry wriables [82].The stability and scalability of reinforcement learning needs to be considered [9].Virtual energy storageGas-			variables [82].	to be considered.
Belt conveyorsvariables in constraints (18)-(19), resulting in low solving efficiency [88].adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [9].Reefer managementTemperature change models of reefer containers are nonlinear and nonconvex [39].The solution accuracy using linear constraints [82].Wehicle schedulingMathematically, the seaport vehicle dispatch energy structure [11].Mathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Mathematically, the seaport reinforcement learning can also be used with its characteristic on agent-environment interaction [124].It's hard to find the equilibrium point of Bilevel or Stackelberg models. The stability and scalability of reinforcement learning needs to be considered [9].Intermodal transportationThere are absolute value functions in constraint (31) [112].The reare many binary variables in constraint (33)-(34), resulting in low solving efficiency [118].The reare many binary variables in low solving efficiency [118].The salopity and scalability of reinforcement learning can also be adopted to solve the problem with a large number of binary variables [124].The transformed hefore reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The transformed hefore reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning can also be adopted to solve problems with a large numbe		There are many binary	Reinforcement learning can be	
Beit conveyors(18)-(19), resulting in low solving efficiency [88].a large number of binary variables [124].of refinit cartning needs to be considered [9].Reefer managementTemperature change models of reefer containers are nonlinear and nonconvex [39].a large number of binary variables [124].The solution accuracy using linearization and convexification nonlinear constraints [82].The solution accuracy using linearization and convexification needs to be considered [82].Vehicle schedulingMathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Mathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Mathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].There are absolute value functions in constraint (31) [112].There are absolute value functions in constraint (31) [112].The reare many binary variables in constraint (32)-(34), resulting in low solving efficiency [118].The reare many binary variables in constraint (36) is bilinear and needs to be constraint (36) is bilinear and needs to be constraint (36) is bilinear and needs to be considered [9].The stability and scalability of reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The transformed model, square method, geometric matential methods [124].Virtual energy storageThere are many binary variables in low solving efficiency [118].Linearization and convexification constraint (36) is bilinear and needs to be solved by clas	D.H.	variables in constraints	adopted to solve problems with	The stability and scalability
Solving efficiency [88].variables [124].Interaction and convexification can be used to transform nonlinear constraints [82].Reefer managementTemperature change models of reefer containers are nonlinear and nonconvex [39].Linearization and convexification nonlinear constraints [82].The solution accuracy using linearization and convexification nonlinear constraints [82].Vehicle schedulingMathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer storageMathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer storageMathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer storageMathematically, the seaport vehicle dispatch energy model (23)-(30) has a two-layer storageMathematically, the seaport vehicle dispatch energy (23)-(30) has a two-layer (23)-(30) has a two-layer (23)-(30) has a two-layer (23)-(34), resulting in low solving efficiency [118].The zero-segmentation method, square method, geometric meaning method can be used to solve absolute value functions in constraint (31) (112].The zero-segmentation method, square method, geometric meaning method can be used to solve absolute value functions. Reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The solution accuracy needs to be considered [9].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before in cansformed before mathematical methods [123].Linearization and convexification the subsolute value functions in constrai	Belt conveyors	(18)- (19) , resulting in low	a large number of binary	or reinforcement learning
Reefer managementTemperature change models of reefer containers are nonlinear and nonconvex [39].Linearization and convexification can be used to transform nonlinear constraints [82]. Bilevel or Stackelberg models can be used to solve the problem with two-layer structure. Furthermore, reinforcement learning can also be used with its characteristic on agent-environment interaction [124].The solution accuracy using linearization and convexification need to be considered [82].Vehicle schedulingMathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Mathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Bilevel or Stackelberg models can be used to solve the problem with two-layer structure. Furthermore, reinforcement learning can also be used with its characteristic on agent-environment interaction [124].It's hard to find the equilibrium point of Bilevel or Stackelberg models. The stability and scalability of reinforcement learning needs to be considered [9].Physical energy storageThere are many binary variables in low solving efficiency [118].Reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [9].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before mathematical methods [123].Inearization and convexification can be used to transform bilinear can be used to transform bilinear terms into linear constraints with the help of auxiliary wriab		solving efficiency [88].	variables [124].	needs to be considered [9].
Reefer managementInterfer containers are nonlinear and nonconvex [39].can be used to transform nonlinear constraints into linear constraints [82].linearization and convexification need to be considered [82].Vehicle schedulingMathematically, the seaport vehicle dispatch energy defined by constraints (23)-(30) has a two-layer structure [11].Mathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Bilevel or Stackelberg models can be used to solve the problem with two-layer structure. Furthermore, reinforcement learning can also be used with its characteristic on agent-environment interaction [124].It's hard to find the equilibrium point of Bilevel or Stackelberg models. The stability and scalability of reinforcement interaction [124].Physical energy storageThere are many binary variables in low solving efficiency [118].Reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning can also be dopted to solve problems with a large number of binary variables [124].The solution accuracy needs to be considered [9].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].The large number of binary variables [82].The solution accuracy needs to be considered [82].		Temperature change models of	Linearization and convexification	The solution accuracy using
Vehicle schedulingand nonconvex [39].nonlinear constraints into linear constraints [82]. Bilevel or Stackelberg models can be used to solve the problem with two-layer structure. Furthermore, reinforcement learning can also be used with its characteristic on agent-environment interaction [124].need to be considered [82].Intermodal transportationThere are absolute value functions in constraint (31) [112].There are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].There are many binary variables in constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].The solved by classical meaning method select problems with a large number of binary variables [82].The solution accuracy needs to be considered [9].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and method select by classical mathematical methods [123].Linearization and convexification can be used to transformed before it can be solved by classical mathematical methods [123].The solve do graph variables [82].The solution accuracy needs to be considered [82].	Reefer management	reefer containers are nonlinear	can be used to transform	linearization and convexification
Vehicle schedulingMathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Intear constraints [82].It's hard to find the equilibrium point of Bilevel or Stackelberg models. The stability and scalability of reinforcement interaction [124].Intermodal transportationThere are absolute value functions in constraint (31) [112].There are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].There are many binary variables in constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].There are for the equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].The solution accuracy needs to be considered [82].The solution accuracy needs to be considered [82].		and nonconvex [39].	nonlinear constraints into	need to be considered [82].
Vehicle schedulingMathematically, the seaport vehicle dispatch energy model defined by constraints (23)-(30) has a two-layer structure [11].Directed is stackenberg models to solve the problem with two-layer structure. Furthermore, reinforcement learning can also be used with its characteristic on agent-environment interaction [124].It's hard to find the equilibrium point of Bilevel or Stackelberg models. The stability and scalability of reinforcement learning needs to be considered [9].Intermodal transportationThere are absolute value functions in constraint (31) [112].The zero-segmentation method, square method, geometric meaning method can be used to solve absolute value functions.The transformed model is a non-convex nonlinear model, which cannot be solved directly [82].Physical energy storageThere are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].Reinforcement learning can abs be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [9].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Linearization and convexification can be used to transform bilinear terms into linear constraints with the help of auxiliary wriables [82].The solution accuracy needs to be considered [82].			Bilevel on Stackelborg models can	
Vehicle dispatch energy vehicle dispatch energy twohcle dispatch energy storageWenicle dispatch energy defined by constraints (23)-(30) has a two-layer structure [11].De dect of both of binary variables interaction [124].point of Bilevel or Stackelberg models. The stability and scalability of reinforcement learning needs to be considered [9].Intermodal transportationThere are absolute value functions in constraint (31) [112].There are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].There are many binary variables in low solving efficiency [118].There are many binary variables in constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].The are for comparison to solve absolute value functions.The solution accuracy needs to be considered [9].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Difference in arg transportationDifference in arg transportationVirtual energy storageSolve absolute value functions in constraint (36) is bilinear and needs to be transformed before with the help of auxiliary wariables [82].Difference in any binary variables to be considered [82].		Mathematically the seaport	be used to solve the problem with	It's hard to find the equilibrium
Vehicle schedulingVehicle schedulingVehicle schedulingVehicle schedulingdefined by constraints (23)-(30) has a two-layer structure [11].of the splet energy storagereinforcement learning can and the splet energy storagemodels. The stability and scalability of reinforcement learning needs to be considered [9].Intermodal transportationThere are absolute value functions in constraint (31) [112].There are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].The reare many binary variables in constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].The solution accuracy needs with the help of auxiliary wariables [82].The solution accuracy needs to be considered [82].		vehicle dispatch energy model	two-layer structure. Furthermore	point of Bilevel or Stackelberg
(23)-(30) has a two-layer structure [11].be used with its characteristic on agent-environment interaction [124].scalability of reinforcement learning needs to be considered [9].Intermodal transportationThere are absolute value functions in constraint (31) [112].be used with its characteristic on agent-environment interaction [124].Scalability of reinforcement learning needs to be considered [9].Physical energy storageThere are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].The reare many binary variables in constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].The solution accuracy needs to be considered [9].Virtual energy storageCas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Linearization and convexification can be used to transform bilinear terms into linear constraints with the help of auxiliary variables [82].The solution accuracy needs to be considered [82].	Vehicle scheduling	defined by constraints	reinforcement learning can also	models. The stability and
structure [11].on agent-environment interaction [124].learning needs to be considered [9].Intermodal transportationThere are absolute value functions in constraint (31) [112].The zero-segmentation method, square method, geometric meaning method can be used to solve absolute value functions.The transformed model is a non-convex nonlinear model, which cannot be solved directly [82].Physical energy storageThere are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].Reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning needs to solve absolute value functions.Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Linearization and convexification can be used to transform bilinear terms into linear constraints with the help of auxiliary variables [82].The solution accuracy needs to be considered [82].		(23)- (30) has a two-layer	be used with its characteristic	scalability of reinforcement
Intermodal transportationThere are absolute value functions in constraint (31) [112].interaction [124].The transformed model is a non-convex nonlinear model, which cannot be solved directly [82].Physical energy storageThere are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].The zero-segmentation method, square method, geometric meaning method can be used to solve absolute value functions.The transformed model is a non-convex nonlinear model, which cannot be solved directly [82].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Linearization and convexification canstraints [82].The solucion accuracy needs to be considered [9].		structure [11].	on agent-environment	learning needs to be
Intermodal transportationThere are absolute value functions in constraint (31) [112].The zero-segmentation method, square method, geometric meaning method can be used to solve absolute value functions.The transformed model is a non-convex nonlinear model, which cannot be solved directly [82].Physical energy storageThere are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].The zero-segmentation method, square method, geometric meaning method can be used to solve absolute value functions.The transformed model is a non-convex nonlinear model, which cannot be solved directly [82].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Linearization and convexification can be used to transform bilinear terms into linear constraints with the help of auxiliaryThe solution accuracy needs to be considered [82].			interaction [124].	considered [9].
Intermodal transportationInterior are associate value functions in constraint (31) [112].square method, geometric meaning method can be used to solve absolute value functions.non-convex nonlinear model, which cannot be solved directly [82].Physical energy storageThere are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].square method, geometric meaning method can be used to solve absolute value functions.non-convex nonlinear model, which cannot be solved directly [82].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Linearization and convexification can be used to transform bilinear terms into linear constraints with the help of auxiliary wriables [82].The solution accuracy needs to be considered [9].		There are absolute value	The zero-segmentation method,	The transformed model is a
transportationIntervention of the bill of the bill of the billmeaning method can be used to solve absolute value functions.which cannot be solved directlyPhysical energy storageThere are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].meaning method can be used to solve absolute value functions.which cannot be solved directlyVirtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Linearization and convexification can be used to transform bilinear terms into linear constraints with the help of auxiliary variables [82].The solution accuracy needs to be considered [9].	Intermodal	functions in constraint (31)	square method, geometric	non-convex nonlinear model,
Physical energy storageThere are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].To solve absolute value functions.[82].Physical energy storageThere are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].Reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [9].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Linearization and convexification can be used to transform bilinear with the help of auxiliary wriables [82].The solution accuracy needs to be considered. With more auxiliary variables, solving efficiency is also a problem	transportation	[112].	meaning method can be used	which cannot be solved directly
Physical energy storageThere are many binary variables in constraints (33)-(34), resulting in low solving efficiency [118].Reinforcement learning can also be adopted to solve problems with a large number of binary variables [124].The stability and scalability of reinforcement learning needs to be considered [9].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Linearization and convexification can be used to transform bilinear with the help of auxiliary wriables [82].The stability and scalability of reinforcement learning needs to be considered [9].		[].	to solve absolute value functions.	[82].
Physical energy storagein constraints (33)-(34), resulting in low solving efficiency [118].also be adopted to solve problems with a large number of binary variables [124].reinforcement learning needs to be considered [9].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Linearization and convexification can be used to transform bilinear with the help of auxiliary variables [82].The solution accuracy needs to be considered [9].	Dhaaiing haar an ara	There are many binary variables	Reinforcement learning can	The stability and scalability of
storagein low solving efficiency [118].problems with a large numberto be considered [9].Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Linearization and convexification can be used to transform bilinear with the help of auxiliaryThe solution accuracy needs to be considered. With more auxiliary variables, solving efficiency is also a problem	r hysical energy	in constraints (33) - (34) , resulting	problems with a large number	reinforcement learning needs
Virtual energy storageGas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods [123].Untable (121) convertication convertication transformed bilinear terms into linear constraints with the help of auxiliaryThe solution accuracy needs to be considered. With more auxiliary variables, solving efficiency is also a problem to be considered [82].	storage	in low solving efficiency [118].	of binary variables [124]	to be considered $[9]$.
Virtual energy storage virtual energy virtual energy		Gas-phase equilibrium	Linearization and convexification	The solution accuracy needs
virtual energy storageneeds to be transformed before it can be solved by classical mathematical methods [123].terms into linear constraints with the help of auxiliary variables [82].auxiliary variables, solving efficiency is also a problem to be considered [82].	37:4	constraint (36) is bilinear and	can be used to transform bilinear	to be considered. With more
storageit can be solved by classical mathematical methods [123].with the help of auxiliary variables [82].efficiency is also a problem to be considered [82].	virtual energy	needs to be transformed before	terms into linear constraints	auxiliary variables, solving
mathematical methods [123]. variables [82]. to be considered [82].	storage	it can be solved by classical	with the help of auxiliary	efficiency is also a problem
		mathematical methods [123].	variables [82].	to be considered [82].

TABLE IV SUMMARY ON MODELS OF PORT INTEGRATED ENERGY SYSTEMS

The above is a storage tank model with "gas-liquid" coupling, where the gas and liquid phases are coupled by the material balance of evaporation $(k_v V_l^t)$ and the total storage volume is fixed (Constraint (37)), while the gas-phase equilibrium constraint (36) is bilinear and needs to be transformed before it can be solved by classical mathematical methods.

D. Summary

Table IV provides an analysis of the port integrated energy system's models on existing challenges, available solutions, and shortcomings of each solution. In summary, there are many binary variables, non-convex and nonlinear terms in formulated port integrated energy models, which result in low solving efficiency and accuracy. These models can be transformed into convex or linear models using linearization and convexification methods [82]. Furthermore, the reinforcement learning method, as an intelligent algorithm, has great potential in solving such models [124].

V. CYBER-PHYSICAL SYSTEM RESILIENCY

A seaport integrated energy system's resilience is determined by the capacity to endure extreme events and then recover back to the pre-disrupted form. In this section, cyber attacks and physical faults in seaports are first discussed. The types of resilience are then classified, including cyber resilience, physical resilience, and cyber-physical resilience. Finally, approaches which can be utilized to enhance the resilience of seaport cyber-physical systems are discussed.

A. Cyber Attacks and Physical Faults

The physical fault and the cyber attack are included in seaports according to the characteristics of the seaport cyber-physical system [125].

Physical faults: Physical faults fall into two categories: relay malfunction and relay rejection [126]. Many causes are resulting in relay malfunction, including wiring errors and field installation wiring errors, insulation reduction or insufficient of the secondary loop, saturation of the core of the current transformer, incorrect wiring of the current transformer, high-intensity electromagnetic interference, etc. Furthermore, there are also many causes resulting in relay rejection, including mismatch with the technical parameters of other equipment, virtual connection and welding of external wiring screws, large operation current setting value, large load current on the load side, wear of mechanical action mechanism and bakelite parts, and poor contact of contacts, etc.

Cyber attack: There are three categories of cyber attacks, including the command injection attack, false injection attack, and replay attack [127]. The false control commands forged by command injection attacks can make the digital relay output incorrect control signals, and make the incorrect operation of port logistic activities which may lead to serious accidents. Malicious false data injected into the digital relay or logistics equipment control centre makes the control available. In a replay attack, data from the previous period is re-sent to control centres of logistic equipment to re-simulate the previous attack.

In addition, integrated cyber-physical attacks are designed to maximize the damage of the attack or hide the previous cyber attack. When a command injection attack is forged to make a digital relay malfunction, the attacker issues a coordinated replay attack to simulate the previous attack for concealing the command injection attack. Furthermore, cyber attacks can be utilized by hackers to hide a physical attack. To be specific, when a circuit breaker is attacked physically, the supervisory control and data acquisition system can fail to monitor the physical destruction as elaborate cyber attacks are launched to conceal the physical attack.

B. Types of Resilience

Cyber resilience: The combination of cyber security, with an emphasis on preventing failures, and cyber risk management, which maintains vital services in the case of cyber attacks, is commonly referred to as "cyber resilience" in modern cyberphysical systems [128]. In port cyber-physical systems, cyber networks include wide-area monitoring systems, energy management systems, and supervisory control and data acquisition systems with the goals of gathering, transmitting, processing, and storing data on energy system operation. Therefore, the cyber resilience of port cyber-physical systems depends on the availability, accuracy, and secrecy of information. A resilient communication network design on the device level was investigated in [129] to ensure the security of communications information and to identify cyberattacks for constructing a cyber network to avoid and avert major failures. Additionally, defence measures against fraudulent data injections were researched in [130] to achieve recovery or reduce the damage when the port cyber system is attacked.

Physical resilience: Energy systems need to recover from high-consequence incidents, according to [131]. Resilience is described as "the ability to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events" in a report by the U.S. National Academy of Sciences [132]. This definition divides resilience into two subcategories: short-term resilience and long-term resilience. Short-term resilience refers to the characteristics that a system should possess before/during/after an event. It also has to do with the system's capacity to withstand and dynamically adjust to such events. Long-term resilience is concerned with the system's capacity to adjust to adverse occurrences in the future. Hardening of the physical infrastructure and extensive system planning are typical measurements.

Cyber-physical resilience: A resilient port cyber-physical system should respond to cyber-physical attacks in real time and mitigate major interruptions of critical services. For general cyber-physical systems, the evaluation of cyber-physical resilience was studied in [133], [134]. A port cyber-physical framework was proposed in [135], which consisted of three parts: system identification, vulnerability analysis, and resilient operation.

C. Analytic Approaches to Assess Resilience

The resilience of port cyber-physical systems was studied via various methodologies, including evaluation, Markov process, optimization, etc [136]. Security assessment metrics and fuzzy Choquet integral approach were utilized in [137] to assess the resilience of cyber-physical systems, which can also be adopted in port cyber-physical system areas. In addition, port device-level resilience strategy can be studied based on examining cyber vulnerabilities and modelling device-level resilience against cyber attacks [129]. The cyber-physical resilience for integrated energy and transport systems can be studied where the infrastructural metrics and operational metrics are integrated through a weighted sum method [138]. Cyber resilience can be evaluated via a systemic impact index and a targeted system performance index [139]. Markov decision processes and Q-learning were useful while assessing the resilience of cyber-physical control systems against attacks. The optimal attack sequence can be modelled and employed to simulate the attacker's problem in [124]. Cyber-physical systems were modelled as linear systems, and methodologies were discussed to synthesize the controllers to guarantee resilience. Hierarchical games and Markovian cyber defence policies can be adopted to maximize system resilience considering the cost of recovery [124]. The resilience analysis framework against denial-of-service cyberattacks can be established based on a stability analysis considering the influences of time-varying denial-of-service incidents. A resilience measure is defined to stand for the input-to-state stability and was quantified by convex optimization techniques [130].

VI. FUTURE ROADMAP AND KEY PROBLEMS

This article has reviewed the detailed models for the physical side of the seaport energy system, but the cyber system of the seaport is still out of the current research scope. In future green seaports, advanced communication and intelligent control technology will be deeply integrated into fundamental physical infrastructure and services of the multi-energy and transportation subsystems, which facilitates more efficient cooperation among subsystems as well as the optimal allocation of schedulable resources. Through efficient information sharing and distributed coordination processes, the superior quality of services and energy management efficiency of seaports can be achieved from a global perspective of the whole system. To fulfil the vision, the future roadmap and potential key problems are summarized as follows:

A. Green Communications in Seaport

The introduction of electrified logistics equipment at ports undoubtedly accelerates the process and increases communication needs. Exponential growth in data and ubiquitous access requirements have triggered a rapid upgrade of rapidly expanding network infrastructure and the corresponding energy needs. The escalation of energy needs in port cyber networks directly leads to increased carbon emissions and has also been regarded as a major threat to environmental protection and sustainable development. Therefore, it becomes urgent for the port cyber system to minimize the electricity bills and achieve the goal of green seaports concerning green communications. Seaport green communication, a research direction towards the development of future cyber architectures and technologies towards high energy efficiency, has become an important trend in the field of port integrated energy research.

The energy consumption load of a port cyber system is characterized by a flexible load. Data to be processed, also called workloads, arriving at the port cyber system can be divided into two categories, including interactive and batch workload [140]. The interactive workloads, also known as delaysensitive workloads, must be processed immediately (typically in a few seconds), such as real-time monitoring and dispatching of electrified equipment in ports. And batch workloads allow a flexible service time that can be delayed by hours, such as the vehicle-job matching and berth allocation given the port transfer jobs in a day-ahead manner. Batch workloads are optimally allocated to different time slots while the energy supply for all the workloads is scheduled based on the operation cost of the port cyber system.

For port green communication, it is critical to achieving the balance between application efficiency, energy efficiency and spectrum efficiency with goals of minimizing data delay, minimizing energy consumption and maximizing achievable rate in the port cyber network [141]. With these three kinds of efficiency, key cyber network performance and cost indicators in seaport areas can be all strung together.

To elaborate on the three kinds of efficiency, cyber network planning, resource management, and physical layer transmission scheme design are future research topics for port green communications in the planning stage. Furthermore, research efforts in the operational stage focus on the cyber-physical management for port integrated energy systems to improve the operational efficiency of the whole system and achieve a green seaport. Specifically, the cyber system first needs to optimally make the workload management to respond to the price signals, and also coordinate with the flexible load dispatch in the port physical system.

B. Hybrid Cyber-Physical Model in Seaport

Future green seaport with cyber-physical integration is essentially a complicated heterogeneous system. The dynamic response and evolution of relevant variables in individual physical subsystems are driven by time, thus can be intuitively modelled by continuous functions of time; However, the measurement, communication and decision-making processes in cyber systems are usually carried out intermittently following the operation and cooperation logic set by human designers, which collaborate with the evolution of physical system discretely to achieve controlling objectives.

Hence, instead of a unilateral physical or cyber system model, a hybrid cyber-physical model is of vital importance in theoretical research of future green seaports, which works as the basis of two fundamental technical requirements:

Deduction of system evolution: The hybrid model depicts the system's evolution of macro (e.g., power or heat flow) and micro (e.g., the operation state of one specific equipment) dynamic processes in standard mathematical formulation, such as algebraic equations or differential equations. Once control logic and the initial state of the seaport system are given, sub-sequential system evolution could be deduced by numerical calculation to predict the operation trend of the system.

Verification of collaboration logic: Coupled continuous and discrete dynamics, and concurrent characteristics of equipment/subsystem interactions are very likely to introduce imperceptible hidden defects into system collaboration logic. Traditional verification method based on model testing is not competent to completely cover and verify all reachable operating states of the system. In this regard, a hybrid model can be utilized for analysis and verification of the system by drawing support from theories in the realm of formal description and verification, which can cover all possible operation states from the theoretical level and guarantees the correctness and reliability of collaboration logic.

C. Economy of Cyber-Physical System in Seaport

Except for the aforementioned obstacles confronted in centralized decision architecture (e.g., massive decision variables and complex optimization model), subsystems in seaports usually pursue separate economic targets and operate under physical dynamics with a diversified time-scale, which makes it naturally suitable to adopt weak-centralized (i.e., decentralized or distributed) architecture to conduct decision and control strategy.

In this regard, multi-agent systems, game theory and distributed optimization methodologies are of great significance for application layer decision processes. Individual software agents make localized decisions selfishly with only limited knowledge of the whole system and finally reach a Pareto-efficiency solution through negotiation (interaction) with neighbour agents, where it is impossible to make any agent better off without making other agents worse off simultaneously, so global welfare of the whole system is guaranteed.

Additionally, each agent should be capable of interpreting their operation condition through information gathered by sensors and autonomously make localized decisions. Hence, sensor fusion, pattern recognition and artificial intelligence-relevant methods should be brought to the research forefront.

D. Resilience of Cyber-Physical System in Seaport

After cyber-physical integration, several different subsystems can adaptively combine and cooperate during a limited period to create a "system of system" to reinforce the seaport's resilience against abnormal operation scenarios. This is one of the most typical features of a cyber-physical system that distinguishes it from conventional systems, where adaptive and flexible system boundaries create enhanced functionality. For instance, when the seaport power subsystem loses connection with the main grid due to a fault and is compelled to work in island operation mode, the thermal subsystem and the power subsystem will temporarily build interaction with each other to make up joint real-time decisions. With the aid of thermal inertia, the thermalelectric coupling load will be capable of providing auxiliary power regulation capacity during the island operation period, which ensures the dynamic balance of the power load in the seaport.

Besides adaptive and flexible system boundaries in application layer services, self-organization characteristics of the communication topology in the network layer are also nonnegligible to ensure stronger system resilience. Even if an unpredictable failure occurs to some communication links, the seaport system can switch to spare communication topology by reconstruction of communication topology, which not only avoids the hindrance of the failure link but also guarantees stable and secure information interaction.

To fulfil these two requirements, technologies enabling distributed administration, and configuration should be paid high attention to, such as relevant research in the realm of ad-hoc communication, proactive & reactive communication path routing protocols and common information models.

VII. CONCLUSION

With the continuous development of electrification and the integration of various heterogeneous energy systems, the port will become a complex "energy-transportation integrated system" in the future. This article first summarizes the development of seaports and uses representatives to analyze the typical zones, energy policy, and development trends. Then, the cyber-physical integration framework within seaport and the corresponding operation strategies are reviewed. After that, models of port integrated energy systems are provided. After comprehensively reviewing current research, this article proposes three key problems for cyber-physical integration within seaport areas: the cyber-physical system for seaports under faults, and the operating framework and indexes.

The article makes recommendations for future research priorities including green communications, port hybrid cyber-physical models, the economy of port cyber-physical systems and the resilience of port cyber-physical systems.

REFERENCES

- T. R. Walker et al., "Environmental effects of marine transportation," in World Seas: An Environmental Evaluation, 2nd ed., C. Sheppard, Ed., New York, NY, USA: Academic Press, 2019, ch. 27, pp. 505–530.
- [2] G. Laporte, "Sustainable shipping: A cross-disciplinary view," *Maritime Econ. Logistics*, vol. 22, no. 2, pp. 326–327, 2020, doi: 10.1057/s41278-020-00159-2.
- [3] E. S. Han, A. Goleman, D. Boyatzis, and R. Mckee, "Review of maritime transport 2020," 2020. [Online]. Available: https://unctad.org/system/ files/official-document/rmt2020_en.pdf
- [4] M. Boile, S. Theofanis, E. Sdoukopoulos, and N. Plytas, "Developing a port energy management plan: Issues, challenges, and prospects," *Transp. Res. Rec. J. Transp. Res. Board*, vol. 2549, pp. 19–28, 2016.
- [5] J.-K. Woo, D. S. H. Moon, and J. S. L. Lam, "The impact of environmental policy on ports and the associated economic opportunities," *Transp. Res.*, *Part Policy Pract.*, vol. 110, pp. 234–242, 2018.
- [6] Y. Y. Wei and J. Lam, "80 million-twenty-foot-equivalent-unit container port sustainability issues in port and coastal development," *Ocean Coastal Manage.*, vol. 71, pp. 13–25, 2013.
- [7] A. Mirakyan and R. De Guio, "Integrated energy planning in cities and territories: A review of methods and tools," *Renewable Sustain. Energy Rev.*, vol. 22, pp. 289–297, 2013.
- [8] N. Liu, L. Zhou, C. Wang, X. Yu, and X. Ma, "Heat-electricity coupled peak load shifting for multi-energy industrial parks: A Stackelberg game approach," *IEEE Trans. Sustain. Energy*, vol. 11, no. 3, pp. 1858–1869, Jul. 2020.
- [9] S. Fang, Y. Xu, S. Wen, T. Zhao, H. Wang, and L. Liu, "Data-driven robust coordination of generation and demand-side in photovoltaic integrated all-electric ship microgrids," *IEEE Trans. Power Syst.*, vol. 35, no. 3, pp. 1783–1795, May 2020.
- [10] Z. Li, Y. Xu, S. Fang, X. Zheng, and X. Feng, "Robust coordination of a hybrid AC/DC multi-energy ship microgrid with flexible voyage and thermal loads," *IEEE Trans. Smart Grid*, vol. 11, no. 4, pp. 2782–2793, Jul. 2020.
- [11] Y. Wang, Y. Xu, K. Liao, and J. Qiu, "New two-layer power control scheme in islanded cyber-physical microgrids," *J. Energy Eng.*, vol. 145, no. 5, 2019, Art. no. 04019017.
- [12] N. Sifakis, S. Konidakis, and T. Tsoutsos, "Hybrid renewable energy system optimum design and smart dispatch for nearly zero energy ports," *J. Cleaner Prod.*, vol. 310, 2021, Art. no. 127397.
- [13] L. Jiang, Z. Bie, T. Long, H. Xie, and X. Wang, "Development model and key technology of integrated energy and transportation system," *Zhong*guo Dianji Gongcheng Xuebao/Proc. Chin. Soc. Elect. Eng., vol. 42, no. 4, pp. 1285–1300, 2022.
- [14] S. Mnasri and M. Alrashidi, "A comprehensive modeling of the discrete and dynamic problem of berth allocation in maritime terminals," *Electronics*, vol. 10, no. 21, 2021, Art. no. 2684. [Online]. Available: https://www.mdpi.com/2079-9292/10/21/2684
- [15] S. H. Chung and K. L. Choy, "A modified genetic algorithm for quay crane scheduling operations," *Expert Syst. Appl.*, vol. 39, no. 4, pp. 4213–4221, 2012.
- [16] N. Ma, C. Zhou, and A. Stephen, "Simulation model and performance evaluation of battery-powered AGV systems in automated container terminals," *Simul. Modelling Pract. Theory*, vol. 106, Jun. 2021, Art. no. 102146.
- [17] M. A. Ertem, M. İşbilir, and A. Ş. Arslan, "Review of intermodal freight transportation in humanitarian logistics," *Eur. Transport Res. Rev.*, vol. 9, no. 1, 2017, Art. no. 10.
- [18] F. D. Kanellos, E. S. M. Volanis, and N. D. Hatziargyriou, "Power management method for large ports with multi-agent systems," *IEEE Trans. Smart Grid*, vol. 10, no. 2, pp. 1259–1268, Mar. 2019.
- [19] S. Fang and H. Wang, Optimization-Based Energy Management for Multi-Energy Maritime Grids. Berlin, Germany:Springer, 2021.
- [20] Ç. Iris and J. S. L. Lam, "A review of energy efficiency in ports: Operational strategies, technologies and energy management systems," *Renewable Sustain. Energy Rev.*, vol. 112, pp. 170–182, May 2019, doi: 10.1016/j.rser.2019.04.069.
- [21] B. Wang, Q. Liu, L. Wang, Y. Chen, and J. Wang, "A review of the port carbon emission sources and related emission reduction technical measures," *Environ. Pollut.*, vol. 320, 2023, Art. no. 121000.
- [22] A. S. Alamoush, F. Ballini, and A. I. Ölçer, "Ports' technical and operational measures to reduce greenhouse gas emission and improve energy efficiency: A review," *Mar. Pollut. Bull.*, vol. 160, 2020, Art. no. 111508.

- [23] N. N. Abu Bakar, N. Bazmohammadi, J. C. Vasquez, and J. M. Guerrero, "Electrification of onshore power systems in maritime transportation towards decarbonization of ports: A review of the cold ironing technology," *Renewable Sustain. Energy Rev.*, vol. 178, 2023, Art. no. 113243.
- [24] D. Zhang et al., "A comprehensive overview of modeling approaches and optimal control strategies for cyber-physical resilience in power systems," *Renewable Energy*, vol. 189, pp. 1383–1406, 2022.
- [25] L. Xu, Q. Guo, Y. Sheng, S. M. Muyeen, and H. Sun, "On the resilience of modern power systems: A comprehensive review from the cyberphysical perspective," *Renewable Sustain. Energy Rev.*, vol. 152, 2021, Art. no. 111642.
- [26] M. K. Hasan, A. A. Habib, Z. Shukur, F. Ibrahim, S. Islam, and M. A. Razzaque, "Review on cyber-physical and cyber-security system in smart grid: Standards, protocols, constraints, and recommendations," *J. Netw. Comput. Appl.*, vol. 209, Nov. 2022, Art. no. 103540, doi: 10.1016/j.jnca.2022.103540.
- [27] T. Wang, Y. Du, D. Fang, and Z. C. Li, "Berth allocation and quay crane assignment for the trade-off between service efficiency and operating cost considering carbon emission taxation," *Transp. Sci.*, vol. 54, no. 5, pp. 1307–1331, 2020.
- [28] D. Kizilay and D. T. Eliiyi, "A comprehensive review of quay crane scheduling, yard operations and integrations thereof in container terminals," *Flexible Serv. Manuf. J.*, vol. 33, no. 1, pp. 1–42, Mar. 2021.
- [29] Ç. Iris and J. S. L. Lam, "Models for continuous berth allocation and quay crane assignment: Computational comparison," in *Proc. IEEE Int. Conf. Ind. Eng. Eng. Manage.*, 2018, pp. 374–378.
- [30] Q. S. Kabir and Y. Suzuki, "Comparative analysis of different routing heuristics for the battery management of automated guided vehicles," *Int. J. Prod. Res.*, vol. 57, no. 2, pp. 624–641, Jan. 2019.
- [31] "2019 air emissions inventory highlights," The port of Los Angeles, Tech. Rep., 2020. [Online]. Available: https://www.portoflosangeles.org/ environment/air-quality/air-emissions-inventory
- [32] N. Tsolakis, D. Zissis, S. Papaefthimiou, and N. Korfiatis, "Towards AI driven environmental sustainability: An application of automated logistics in container port terminals," *Int. J. Prod. Res.*, vol. 60, no. 14, pp. 4508–4528, 2022.
- [33] L. Zhen, S. Lin, and C. Zhou, "Green port oriented resilience improvement for traffic-power coupled networks," *Rel. Eng. Syst. Saf.*, vol. 225, 2022, Art. no. 108569.
- [34] J. Froese, S. Töter, and I. Erdogan, "Green efforts green and effective operations at terminals and in ports Recommendations Manual for Terminals,", *Community Res. Develop. Inf. Serv.*, 2012. [Online]. Available: https://cordis.europa.eu/project/id/285687/reporting/fr
- [35] L. He, R. Chiong, and W. Li, "Energy-efficient open-shop scheduling with multiple automated guided vehicles and deteriorating jobs," J. Ind. Inf. Integration, vol. 30, 2022, Art. no. 100387.
- [36] J. Schmidt, C. Meyer-Barlag, M. Eisel, L. M. Kolbe, and H. J. Appelrath, "Using battery-electric AGVs in container terminals-assessing the potential and optimizing the economic viability," *Res. Transp. Bus. Manage.*, vol. 17, pp. 99–111, 2015, doi: 10.1016/j.rtbm.2015.09.002.
- [37] X. Zhan, L. Xu, J. Zhang, and A. Li, "Study on AGVs battery charging strategy for improving utilization," *Procedia CIRP*, vol. 81, pp. 558–563, 2019.
- [38] J. H. van Duin, H. H. Geerlings, A. A. Verbraeck, and T. T. Nafde, "Cooling down: A simulation approach to reduce energy peaks of reefers at terminals," *J. Cleaner Prod.*, vol. 193, pp. 72–86, 2018.
- [39] Y.-S. Moon et al., "Real-time management system of reefer container based on IoT," *J. Korea Inst. Inf. Commun. Eng.*, vol. 19, pp. 2093–2099, Aug. 2015.
- [40] R. Asariotis et al., "Review of maritime transport 2015," 2015. [Online]. Available: https://unctad.org/system/files/official-document/ rmt2015_en.pdf
- [41] C. Zhou, S. Zhu, M. G. H. Bell, L. H. Lee, and E. P. Chew, "Emerging technology and management research in the container terminals: Trends and the COVID-19 pandemic impacts," *Ocean Coast. Manag.*, vol. 230, 2022, Art. no. 106318, doi: 10.1016/j.ocecoaman.2022.106318.
- [42] R. Pei, J. Xie, H. Zhang, K. Sun, Z. Wu, and S. Zhou, "Robust multi-layer energy management and control methodologies for reefer container park in port terminal," *Energies*, vol. 14, Jul. 2021, Art. no. 4456.
- [43] T. Shinoda and M. Budiyanto, "Energy saving effect of roof shade for reefer container in marine container terminal," J. Jpn. Inst. Navigation, vol. 134, pp. 103–113, Jul. 2016.

- [44] M. Abdelmoniem, M. Gheith, and N. Harraz, "A new formulation for the yard crane scheduling problem with energy consumption considerations," in *Proc. Towards Digit. World Ind. X.O - Proc. 29th Int. Conf. Int. Assoc. Manage. Technol.*, 2020, pp. 400–413.
- [45] M. Wang, C. Zhou, and A. Wang, "A cluster-based yard template design integrated with yard crane deployment using a placement heuristic," *Transp. Res. Part E: Logistics Transp. Rev.*, vol. 160, 2022, Art. no. 102657.
- [46] W. Cui and L. Zhen, "Minimizing the total energy consumption of yard crane under the peak demand constraint," *Xitong Gongcheng Lilun yu Shijian/Syst. Eng. Theory Pract.*, vol. 41, no. 2, pp. 358–369, 2021.
- [47] S. Chen, A. J. Conejo, R. Sioshansi, and Z. Wei, "Operational equilibria of electric and natural gas systems with limited information interchange," *IEEE Trans. Power Syst.*, vol. 35, no. 1, pp. 662–671, Jan. 2020.
- [48] Y. Wen, X. Qu, W. Li, X. Liu, and X. Ye, "Synergistic operation of electricity and natural gas networks via ADMM," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 4555–4565, Sep. 2018.
- [49] J. Twidell and T. Weir, "Renewable energy resources: 2nd edition," Forschungen Und Berichte, vol. 7, pp. 68–84, 2005.
- [50] I. Seddiek, "Application of renewable energy technologies for ECOfriendly sea ports," *Ships Offshore Struct.*, vol. 15, pp. 1–10, Dec. 2019.
- [51] G. Buiza, S. Cepolina, A. Dobrijevic, M. del Mar Cerbán, O. Djordjevic, and C. González-Gaya, "Current situation of the Mediterranean container ports regarding the operational, energy and environment areas," in *Proc. Int. Conf. Ind. Eng. Syst. Manage.*, 2015, pp. 530–536.
- [52] "Jurong port starts world's largest port-based solar facility," 2016. [Online]. Available: https://www.businesstimes.com.sg/energycommodities/jurong-port-starts-worlds-largest-port-based-solarfacility
- [53] R. Cascajo, E. Garcia, E. Quiles Cucarella, A. Correcher, and F. Morant, "Integration of marine wave energy converters into seaports: A case study in the port of Valencia," *Energies*, vol. 12, Feb. 2019, Art. no. 787.
- [54] "Geothermal energy development at Port of Rotterdam, Netherlands," 2020. [Online]. Available: https://dredgewire.com/geothermal-energydevelopment-at-port-of-rotterdam-netherlands/
- [55] "Geothermal energy development at port of rotterdam, Netherlands," 2020. [Online]. Available: https://dredgewire.com/geothermal-energydevelopment-at-port-of-rotterdam-netherlands/
- [56] "China enters a new low-sulphur shipping era," 2020. [Online]. Available: https://chinadialogueocean.net/13818-china-enters-anew-low-sulphur-shipping-era/
- [57] H. Yang et al., "Optimal planning of local biomass-based integrated energy system considering anaerobic co-digestion," *Appl. Energy*, vol. 316, 2022, Art. no. 119075.
- [58] "Hamburg hydrogen network established to promote hydrogen and reduce emissions," 2021. [Online]. Available: https://www.h2view.com/story/hamburg-hydrogen-network-established-to-promotehydrogen-and-reduce-emissions/
- [59] N. Ash and T. Scarbrough, "Sailing on solar: Could green ammonia decarbonise international shipping," 2019.
- [60] T. T. Khanh, "Study of electrical usage and demand at the container terminal," Ph.D. dissertation, Deakin Univ., Geelong, VIC, Australia, 2012.
- [61] G. Parise and A. Honorati, "Port cranes with energy balanced drive," in Proc. IEEE AEIT Annu. Conf. - From Res. Ind.: Need More Effective Technol. Transfer, 2014, pp. 1–5.
- [62] M. Sadiq et al., "Future greener seaports: A review of new infrastructure, challenges, and energy efficiency measures," *IEEE Access*, vol. 9, pp. 75568–75587, 2021.
- [63] "Next gen multipurpose port | Jurong Port Singapore," 2023. [Online]. Available: https://www.jp.com.sg/
- [64] Y. Wang, T. L. Nguyen, Y. Xu, Z. Li, Q.-T. Tran, and R. Caire, "Cyberphysical design and implementation of distributed event-triggered secondary control in islanded microgrids," *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 5631–5642, Nov./Dec. 2019.
- [65] A. Mao, T. Yu, Z. Ding, S. Fang, J. Guo, and Q. Sheng, "Optimal scheduling for seaport integrated energy system considering flexible berth allocation," *Appl. Energy*, vol. 308, Feb. 2022, Art. no. 118386.
- [66] T. L. Nguyen, Y. Wang, Q. T. Tran, R. Caire, Y. Xu, and C. Gavriluta, "A distributed hierarchical control framework in islanded microgrids and its agent-based design for cyber-physical implementations," *IEEE Trans. Ind. Electron.*, vol. 68, no. 10, pp. 9685–9695, Oct. 2021.

- [67] Z. Huang, D. Liu, G. Chen, J. Weng, H. Yin, and Z. Wang, "The evolution mechanism of the cyber-physical cascading failure of power distribution system based on event-driven," *Electric Power Eng. Technol.*, vol. 41, no. 3, pp. 2–13, 2022.
- [68] Y. Li, Z. Li, F. Wen, and M. Shahidehpour, "Privacy-preserving optimal dispatch for an integrated power distribution and natural gas system in networked energy hubs," *IEEE Trans. Sustain. Energy*, vol. 10, no. 4, pp. 2028–2038, Oct. 2019.
- [69] M. S. Khan, S. Effendy, I. A. Karimi, and A. Wazwaz, "Improving design and operation at LNG regasification terminals through a corrected storage tank model," *Appl. Thermal Eng.*, vol. 149, pp. 344–353, 2019.
- [70] M. Götz et al., "Renewable power-to-gas: A technological and economic review," *Renewable Energy*, vol. 85, pp. 1371–1390, 2016.
- [71] Y. Xue, Z. Pan, B. Wang, H. Sun, and Q. Guo, "Security assessment module in integrated energy management system: Development and application," *Dianwang Jishu/Power Syst. Technol.*, vol. 45, no. 2, pp. 437–446, 2021.
- [72] C. Bierwirth and F. Meisel, "A follow-up survey of berth allocation and quay crane scheduling problems in container terminals," *Eur. J. Oper. Res.*, vol. 244, no. 3, pp. 675–689, 2015.
- [73] Y. Mu et al., "Optimal scheduling method for belt conveyor system in coal mine considering silo virtual energy storage," *Appl. Energy*, vol. 275, 2020, Art. no. 115368.
- [74] P. Wang, Vehicle Scheduling Problem in Terminals: A Review (Lecture Notes in Computer Science Series), B. Ben Hedia, Y.-F. Chen, G. Liu, and Z. Yu, Eds., vol. 12519. Cham, Switzerland: Springer Int. Publishing, 2020.
- [75] Y. Kazemi and J. Szmerekovsky, "Modeling downstream petroleum supply chain: The importance of multi-mode transportation to strategic planning," *Transp. Res. Part E: Logistics Transp. Rev.*, vol. 83, pp. 111–125, 2015.
- [76] M. Wang, Y. Mu, X. Meng, H. Jia, X. Wang, and X. Huo, "Optimal scheduling method for integrated electro-thermal energy system considering heat transmission dynamic characteristics," *Dianwang Jishu/Power Syst. Technol.*, vol. 44, no. 1, pp. 132–140, 2020.
- [77] X. Zhu, J. Yang, Y. Liu, C. Liu, B. Miao, and L. Chen, "Optimal scheduling method for a regional integrated energy system considering joint virtual energy storage," *IEEE Access*, vol. 7, pp. 138260–138272, 2019.
- [78] M. Zeng, Y. Liu, P. Zhou, Y. Wang, and M. Hou, "Review and prospects of integrated energy system modeling and benefit evaluation," *Dianwang Jishu/Power Syst. Technol.*, vol. 42, no. 6, pp. 1697–1708, 2018.
- [79] Y. Peng, X. Zhao, T. Zuo, W. Wang, and X. Song, "A systematic literature review on port LNG bunkering station," *Transp. Res. Part D: Transport Environ.*, vol. 91, 2021, Art. no. 102704.
- [80] Z. Li, W. Wu, M. Shahidehpour, J. Wang, and B. Zhang, "Combined heat and power dispatch considering pipeline energy storage of district heating network," *IEEE Trans. Sustain. Energy*, vol. 7, no. 1, pp. 12–22, Jan. 2016.
- [81] G. O. Brown, "The history of the Darcy-Weisbach equation for pipe flow resistance," in *Proc. Conf. Environ. Water Resour. Hist.*, 2002, pp. 34–43.
- [82] S. Fang, S. Zhang, T. Zhao, and R. Liao, "Optimal power-hydrogen networked flow scheduling for residential Carpark with convex approximation," *IEEE Trans. Ind. Appl.*, vol. 58, no. 2, pp. 2751–2759, Mar./Apr. 2022.
- [83] T. Ding, Y. Xu, W. Wei, and L. Wu, "Energy flow optimization for integrated power-gas generation and transmission systems," *IEEE Trans. Ind. Informat.*, vol. 16, no. 3, pp. 1677–1687, Mar. 2020.
- [84] G. Venturini, Ç. Iris, C. A. Kontovas, and A. Larsen, "The multi-port berth allocation problem with speed optimization and emission considerations," *Transp. Res. Part D: Transport Environ.*, vol. 54, pp. 142–159, 2017.
- [85] X. Xiang, C. Liu, and L. Miao, "A bi-objective robust model for berth allocation scheduling under uncertainty," *Transp. Res. Part E: Logistics Transp. Rev.*, vol. 106, pp. 294–319, 2017.
- [86] S. Fang, H. Wang, C. Shang, T. Zhao, and J. Lv, "A decision-making method for berthed electric-ships based on generalized Nash game," in *Proc. IET Conf. Pub.*, vol. 2019, 2019, Art. no. CP764.
- [87] G. Song and W. Song, "Determination and review on calculation method of cross-sectional area of carrying material at belt conveyor," *J. China Coal Soc.*, vol. 42, pp. 556–561, 2017.
- [88] S. Zhang and X. Xia, "Optimal control of operation efficiency of belt conveyor systems," *Appl. Energy*, vol. 87, no. 6, pp. 1929–1937, 2010.

- [89] G. Zsembinszki, P. Moreno, C. Solé, A. Castell, and L. F. Cabeza, "Numerical model evaluation of a PCM cold storage tank and uncertainty analysis of the parameters," *Appl. Thermal Eng.*, vol. 67, no. 1, pp. 16–23, 2014.
- [90] K. K. Sørensen, "Model based control of reefer container systems," Ph.D. dissertation, Aalborg Univ., Aalborg, Denmark, 2013.
- [91] L. J. S. Lukasse, M. B. Baerentz, and J. E. De Kramer-Cuppen, "Quest II: Reduction of CO₂ emissions of reefer containers," 2011, Art. no. 1854. [Online]. Available: https://www.wur.nl/upload_mm/0/0/7/7f5833fb-3654-4f90-b8e1-34cff1ffea5d_ICR2011_FullPaper_Quest2v2_0.pdf
- [92] "Emerson climate technologies Europe, select 8," 2014. [Online]. Available: https://climate.emerson.com/en-us
- [93] "Star cool CA system on general release," 2012. [Online]. Available: http://www.worldcargonews.com/htm/w20120229.618622.htm
- [94] "Pidentec Solutions CTAS launches 7.0 reefer system to automate entry-to-exit refrigerated container monitoring in ports," 2016. [Online]. Available: http://www.pema.org/3227/identec-solutions-launches-ctas-7-0-reefer-system-to-automateentry-to-exit-refrigerated-containermonitoring-in-ports/
- [95] S. J. James, C. James, and J. A. Evans, "Modelling of food transportation systems—A review," *Int. J. Refrigeration*, vol. 29, no. 6, pp. 947–957, 2006.
- [96] H. Niu, X. Zhou, and X. Tian, "Coordinating assignment and routing decisions in transit vehicle schedules: A variable-splitting Lagrangian decomposition approach for solution symmetry breaking," *Transp. Res. Part B: Methodological*, vol. 107, pp. 70–101, 2018.
- [97] Ç. Iris, J. Christensen, D. Pacino, and S. Ropke, "Flexible ship loading problem with transfer vehicle assignment and scheduling," *Transp. Res. Part B: Methodological*, vol. 111, pp. 113–134, 2018.
- [98] B. Yan, X. Zhu, D. H. Lee, J. G. Jin, and L. Wang, "Transshipment operations optimization of sea-rail intermodal container in seaport rail terminals," *Comput. Ind. Eng.*, vol. 141, 2020, Art. no. 106296.
- [99] S. Fazi, J. C. Fransoo, T. Van Woensel, and J. X. Dong, "A variant of the split vehicle routing problem with simultaneous deliveries and pickups for inland container shipping in dry-port based systems," *Transp. Res. Part E: Logistics Transp. Rev.*, vol. 142, 2020, Art. no. 102057.
- [100] D. Kress, S. Meiswinkel, and E. Pesch, "Straddle carrier routing at seaport container terminals in the presence of short term quay crane buffer areas," *Eur. J. Oper. Res.*, vol. 279, no. 3, pp. 732–750, 2019.
- [101] D. Strelnikov and J. Rudnitckaia, "Finding an optimal route of a consignment in a seaport," in *Proc. IEEE 4th Int. Conf. Intell. Transp. Eng.*, 2019, pp. 29–33.
- [102] R. Wibisono, T. J. Ai, and D. Yuniartha, "Fleet sizing of automated material handling using simulation approach," in *Proc. IOP Conf. Ser.*: *Mater. Sci. Eng.*, 2018, vol. 319, Art. no. 12030.
- [103] S. L. Gobal and R. G. Kasilingam, "A simulation model for estimating vehicle requirements in automated guided vehicle systems," *Comput. Ind. Eng.*, vol. 21, no. 1, pp. 623–627, 1991.
 [104] C. Wanan and W. Bin, "Vehicle dispatching under the shortest path and
- [104] C. Wanan and W. Bin, "Vehicle dispatching under the shortest path and port centralization," in *Proc. IEEE 4th Int. Symp. Knowl. Acquisition Model.*, 2011, pp. 139–142.
- [105] P.-H. Koo, "Dispatching transport vehicles in maritime container terminals," *Int. J. Bus. Tourism Appl. Sci.*, vol. 1, no. 1, pp. 90–97, 2013.
- [106] R. Choe, J. Kim, and K. R. Ryu, "Online preference learning for adaptive dispatching of AGVs in an automated container terminal," *Appl. Soft Comput. J.*, vol. 38, pp. 647–660, 2016.
- [107] Y. Zhang, L.-L. Li, H. C. Lin, Z. Ma, and J. Zhao, "Development of path planning approach using improved A-star algorithm in AGV system," J. *Internet Technol.*, vol. 20, pp. 915–924, 2019.
- [108] J.-H. Chuang and N. Ahuja, "An analytically tractable potential field model of free space and its application in obstacle avoidance," *IEEE Trans. Syst., Man, Cybern., Part B*, vol. 28, no. 5, pp. 729–736, Oct. 1998.
- [109] C. Qian, Z. Qisong, and H. Li, "Improved artificial potential field method for dynamic target path planning in LBS," in *Proc. IEEE Chin. Control Decis. Conf.*, 2018, pp. 2710–2714.
- [110] J. Yu, Y. Sun, X. Ruan, and Y. Zhang, "Research on path planning for robots based on PSO optimization for fuzzy controller," in *Proc. IEEE* 11th World Congr. Intell. Control Automat., 2014, pp. 5293–5298.
- [111] Kenworth Truck Co., "Port of Los Angeles rolls out hydrogen fuel cell electric freight demonstration," 2021. [Online]. Available: https://www.portoflosangeles.org/references/2021-news-releases/ news_060721_zanzeff
- [112] B. Yan, "Optimization of train handling operations for sea- rail intermodal container transportation in seaport railway terminals," Ph.D. dissertation, Beijing Jiaotong Univ., Beijing, China, 2020.

- [113] J. Aghaei and M. I. Alizadeh, "Multi-objective self-scheduling of CHP (combined heat and power)-based microgrids considering demand response programs and ESSs (energy storage systems)," *Energy*, vol. 55, pp. 1044–1054, 2013.
- [114] W. Hu, P. Wang, and H. B. Gooi, "Towards optimal energy management of microgrids with a realistic model," in *Proc. IEEE Power Syst. Comput. Conf.*, 2016, pp. 1–7.
- [115] Y. Wang et al., "A comprehensive review of battery modeling and state estimation approaches for advanced battery management systems," *Renewable Sustain. Energy Rev.*, vol. 131, 2020, Art. no. 110015.
- [116] X. Tan, Q. Li, and H. Wang, "Advances and trends of energy storage technology in microgrid," *Int. J. Elect. Power Energy Syst.*, vol. 44, no. 1, pp. 179–191, 2013.
- [117] M. Ghofrani, A. Arabali, M. Etezadi-Amoli, and M. S. Fadali, "A framework for optimal placement of energy storage units within a power system with high wind penetration," *IEEE Trans. Sustain. Energy*, vol. 4, no. 2, pp. 434–442, Apr. 2013.
- [118] Y. He, M. Shahidehpour, Z. Li, C. Guo, and B. Zhu, "Robust constrained operation of integrated electricity-natural gas system considering distributed natural gas storage," *IEEE Trans. Sustain. Energy*, vol. 9, no. 3, pp. 1061–1071, Jul. 2018.
- [119] J. Wang, X. Xie, Y. Lu, B. Liu, and X. Li, "Thermodynamic performance analysis and comparison of a combined cooling heating and power system integrated with two types of thermal energy storage," *Appl. Energy*, vol. 219, pp. 114–122, 2018.
- [120] L. van Biert, M. Godjevac, K. Visser, and P. V. Aravind, "A review of fuel cell systems for maritime applications," *J. Power Sources*, vol. 327, pp. 345–364, 2016.
- [121] S. Fang, Y. Fang, H. Wang, and L. Liu, "Optimal heterogeneous energy storage management for multienergy cruise ships," *IEEE Syst. J.*, vol. 14, no. 4, pp. 4754–4764, Dec. 2020.
- [122] Z. Qiao, Q. Guo, H. Sun, and T. Sheng, "Multi-time period optimized configuration and scheduling of gas storage in gas-fired power plants," *Appl. Energy*, vol. 226, pp. 924–934, 2018.
- [123] S. Fang, C. Wang, Y. Lin, and C. Zhao, "Optimal energy scheduling and sensitivity analysis for integrated power-water-heat systems," *IEEE Syst. J.*, to be published, doi: 10.1109/JSYST.2021.3127934.
- [124] S. Lakshminarayana, J. S. Karachiwala, T. Z. Teng, R. Tan, and D. K. Y. Yau, "Performance and resilience of cyber-physical control systems with reactive attack mitigation," *IEEE Trans. Smart Grid*, vol. 10, no. 6, pp. 6640–6654, Nov. 2019.
- [125] D. Wei, Y. Lu, M. Jafari, P. M. Skare, and K. Rohde, "Protecting smart grid automation systems against cyberattacks," *IEEE Trans. Smart Grid*, vol. 2, no. 4, pp. 782–795, Dec. 2011.
- [126] H. Farzin, M. Monadi, M. Fotuhi-Firuzabad, and M. Savaghebi, "A reliability model for overcurrent relays considering harmonic-related malfunctions," *Int. J. Elect. Power Energy Syst.*, vol. 131, 2021, Art. no. 107093.
- [127] T. L. Zhou, K. S. Xiahou, L. L. Zhang, and Q. H. Wu, "Multiagent-based hierarchical detection and mitigation of cyber attacks in power systems," *Int. J. Elect. Power Energy Syst.*, vol. 125, 2021, Art. no. 106516.
- [128] N. Jacobs, S. Hossain-Mckenzie, and E. Vugrin, "Measurement and analysis of cyber resilience for control systems: An illustrative example," in *Proc. IEEE Conf. Resilience Week*, 2018, pp. 38–46.
- [129] V. Venkataramanan, A. K. Srivastava, A. Hahn, and S. Zonouz, "Measuring and enhancing microgrid resiliency against cyber threats," *IEEE Trans. Ind. Appl.*, vol. 55, no. 6, pp. 6303–6312, Nov./Dec. 2019.
 [130] J. Liu, X. Lu, and J. Wang, "Resilience analysis of DC microgrids
- [130] J. Liu, X. Lu, and J. Wang, "Resilience analysis of DC microgrids under denial of service threats," *IEEE Trans. Power Syst.*, vol. 34, no. 4, pp. 3199–3208, Jul. 2019.
- [131] U. S. D. of Energy, "North American energy resilience model," Sandia Nat. Lab. (SNL-NM), Albuquerque, NM, USA, Tech. Rep. SAND2021-3075PE, 2019. [Online]. Available: https://www.energy. gov/oe/downloads/north-american-energy-resilience-model-july-2019
- [132] E. National Academies of Sciences and Medicine, Enhancing the Resilience of the Nation's Electricity System. New York, NY, USA:Academic Press, 2017. [Online]. Available: https: //nap.nationalacademies.org/catalog/24836/enhancing-the-resilienceof-the-nations-electricity-system
- [133] Y. Mussard-Afcari, D. B. Rawat, and M. Garuba, "Data validation and correction for resiliency in mobile cyber-physical systems," in *Proc. IEEE* 16th Annu. Consum. Commun. Netw. Conf., 2019, pp. 1–4.

- [134] S. Mouelhi, M. E. Laarouchi, D. Cancila, and H. Chaouchi, "Predictive formal analysis of resilience in cyber-physical systems," *IEEE Access*, vol. 7, pp. 33741–33758, 2019.
- [135] R. Arghandeh, A. Von Meier, L. Mehrmanesh, and L. Mili, "On the definition of cyber-physical resilience in power systems," *Renewable Sustain. Energy Rev.*, vol. 58, pp. 1060–1069, 2016.
- [136] S. Paul, F. Ding, K. Utkarsh, W. Liu, M. J. O'Malley, and J. Barnett, "On vulnerability and resilience of cyber-physical power systems: A review," *IEEE Syst. J.*, vol. 16, no. 2, pp. 2367–2378, Jun. 2022.
- [137] V. Venkataramanan, A. Hahn, and A. Srivastava, "CP-SAM: Cyberphysical security assessment metric for monitoring microgrid resiliency," *IEEE Trans. Smart Grid*, vol. 11, no. 2, pp. 1055–1065, Mar. 2020.
- [138] S. Zuloaga, P. Khatavkar, L. Mays, and V. Vittal, "Resilience of cyberenabled electrical energy and water distribution systems considering infrastructural robustness under conditions of limited water and/or energy availability," *IEEE Trans. Eng. Manage.*, vol. 69, no. 3, pp. 639–655, Jun. 2022.
- [139] S. Hossain-McKenzie, C. Lai, A. Chavez, and E. Vugrin, "Performancebased cyber resilience metrics: An applied demonstration toward moving target defense," in *Proc. IEEE 44th Annu. Conf. Ind. Electron. Soc.*, 2018, pp. 766–773.
- [140] T. Chen, X. Wang, and G. B. Giannakis, "Cooling-aware energy and workload management in data centers via stochastic optimization," *IEEE J. Sel. Topics Signal Process.*, vol. 10, no. 2, pp. 402–415, Mar. 2016.
- [141] Y. Chen, S. Zhang, S. Xu, and G. Y. Li, "Fundamental trade-offs on green wireless networks," *IEEE Commun. Mag.*, vol. 49, no. 6, pp. 30–37, Jun. 2011.



Ying Lu (Student Member, IEEE) received the B.S. and M.S. degrees in electrical engineering from North China Electric Power University, Beijing, China, in 2016 and 2020, respectively. She is currently working toward the Ph.D. degree with the School of Electrical Engineering, Chongqing University, Chongqing, China. Her research interests include optimization and reinforcement learning, with applications to seaport energy-transport–information nexus.



Sidun Fang (Senior Member, IEEE) was born in Chongqing, China, in 1991. He received the B.E. degree from the School of Electrical Engineering, Chongqing University, Chongqing, China, in 2012, and the Ph.D. degree in power system and its automation from the School of Electronics Information and Electrical Engineering, Shanghai Jiao Tong University, Shanghai, China, in 2017. He is currently a full Professor in Chongqing University, and his research interests include integrated energy system and

energy-transport integration. Dr. Fang was the recipient of the Outstanding Graduate Prize of Shanghai Jiao Tong University. His doctoral dissertation was nominated as the Excellent Dissertation Papers in Shanghai Jiao Tong University in 2017. He is also an Associate Editor for IEEE Transactions on Industrial Cyber-Physical Systems, IEEE Transactions on Industry Applications and IET Renewable Power Generation.



Tao Niu (Member, IEEE) received the B.S. and Ph.D. degrees from the Department of Electrical Engineering, Tsinghua University, Beijing, China, in 2014 and 2019, respectively. He is currently an Assistant Professor with Chongqing University, Chongqing, China. His research interests include voltage security region, automatic reactive power voltage control, renewable generation integration, and reactive power analvsis of hybrid AC/DC system.



Chen Guanhong (Student Member, IEEE) received the B.S. and Ph.D. degrees from Shanghai Jiao Tong University, Shanghai, China, in 2016 and 2023, respectively. He is currently a Hongshen Lecturer with Electrical Engineering Department, Chongqing University, Chongqing, China. His research interests include smart grid, cyber-physical systems for power grid, and distributed optimization and control.



Ruijin Liao received the B.E. degree in electrical engineering from Chongqing University, Chongqing, China, in 1985, the M.E. degree in electrical engineering from Xi'an Jiao Tong University, Xi'an, China, in 1988, and the Ph.D. degree in electrical engineering from Chongqing University in 2003. He is currently a Full Professor with the School of Electrical Engineering, Chongqing University, and the Vice President of Chongqing University. He is also a Distinguished Professor with Changjiang Scholars of

China. He has been selected as Highly Cited Author by Elsevier in 2019 and 2020. His research interests include electric breakdown, equipment aging, power transformer, and safety of energy systems. Dr. Liao is an Associate Editor for IET *High Voltage*, Co-Editorin-Chief of *High Voltage Technology*, and the Editorial Board Member of *CSEE Journal of Power and Energy Systems, Proceedings of CSEE*, and *Transactions of China Electrotechnical Society*. He was the recipient of the National Outstanding Youth Fund of China, Leader of the Natural Fund's Innovative Research Group of High-Voltage Transmission and Distribution Equipment Safety Theory and Technology of China, and Distinguished Professor of Two-River Scholars in Chongqing of China. He is also a Member of GIGRE SC-C4 and CIGRE China National Committee.