Intelligent Traffic Organization for Sea Ports: Fusing Multi-Source Data for Resource Allocation and Scheduling

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Abstract: Reliable autonomous traffic organization is critical for smart ports operating under dynamic ocean conditions. This study proposes a comprehensive framework for sea port scheduling based on Multi-Source Information Fusion (MSIF). To address the challenge of fusing heterogeneous data streams-including vessel trajectories, resource availability, and environmental constraints-a Mixed-Integer Programming (MIP) formulation is first established. Subsequently, a high-fidelity digital twin integrating Cellular Automata (CA) and Multi-Agent Systems (MAS) is developed to simulate heterogeneous cooperative behaviours and stochastic uncertainties. Crucially, a novel Simulation-based Multi-Objective Genetic Algorithm (SMOGA) serves as the autonomous decision-making engine, fusing simulation feedback with evolutionary search to optimize vessel sequencing and resource allocation dynamically. Validated with real-world data from Tianjin Port, the framework outperforms both traditional rules and modern swarm intelligence algorithms, increasing throughput by 16.5% and reducing turnaround time by 11.7%. This research demonstrates how fusing multi-scale information into an intelligent evolutionary framework enables robust, autonomous decision-making in congested maritime environments.

Keywords: Autonomous Systems; Multi-Source Information Fusion; Port Traffic Management; Simulation-based Multi-Objective Genetic Algorithm (SMOGA); Cooperative Autonomy

1. Introduction

Maritime transportation plays a pivotal role in the global economy, accounting for over 80% of the world's trade as highlighted by the United Nations Conference on Trade and Development (*Towards a green and just transition*, 2023). This significant reliance on maritime transport underscores the critical importance of efficient and autonomous port operations. The urgency for intelligent optimization becomes particularly evident considering the substantial costs incurred by vessel operators, which, as noted by Al-Dhaheri and Diabat (2017), can escalate to as much as 4000 USD per hour during port waiting times. These delays not only impact the profitability of shipping companies but also indicate a failure in processing complex environmental data, leading to congestion and inefficiencies. Additionally, the financial implications for seaport operators are considerable. The cost of constructing berths and acquiring resources represents a massive capital investment. Therefore, the efficient utilization of these resources through robust Multi-Source Information Fusion (MSIF) is paramount to maintaining economic viability. Ineffective resource

allocation and traffic organisation often stem from a lack of integrated situational awareness, leading to operational bottlenecks and diminishing the quality of service.

However, conventional optimization approaches often struggle to capture the full complexity of modern seaports operating under dynamic ocean conditions. They typically focus on isolated sub-problems — such as berth allocation or channel scheduling — and rely on simplified mathematical models. These models frequently fail to fuse the stochastic elements inherent in maritime traffic, such as unpredictable vessel arrival times, sensor data noise, and environmental disruptions. Furthermore, disparate data sources regarding channel status, pilot availability, and vessel dynamics are often treated independently, making it difficult to simultaneously balance conflicting objectives like minimizing waiting times while ensuring safety. This disconnection between simplified models and the complex, multi-source reality limits the practical applicability of their solutions in autonomous systems.

To address these challenges, this study formulates the port traffic organization problem as a comprehensive multi-objective optimization task driven by multi-source information fusion. The core decision variables optimized in the proposed autonomous framework include: (1) the sequence of vessel entry and exit, determining the priority of service based on fused traffic data; (2) the specific arrival time at the anchorage, regulating the flow of incoming traffic; and (3) the waiting duration at both anchorage and berths, which acts as a buffer against the uncertainty in resource availability. By dynamically adjusting these variables, the SMOGA (Simulation-based Multi-Objective Genetic Algorithm) framework aims to achieve three key objectives: maximizing throughput, minimizing the peak usage of auxiliary resources, and reducing the average vessel turnaround time.

This paper proposes a strictly validated framework to the field of maritime logistics and autonomous systems by addressing the intricate challenges of traffic organisation and resource allocation in busy port waters. The key contributions are as follows:

a. The development of a MIP model tailored for busy waterways, which comprehensively fuses the constraints of various multi-source inputs within the port navigation system. This includes anchorage capacities, channel rules, berth status, and dynamic auxiliary resources (pilots and tugboats). The model adeptly integrates these diverse information sources, offering a holistic approach to optimising traffic organisation in congested maritime environments.

b. The establishment of a port navigation simulation model, innovatively utilising Cellular Automaton (CA) and a Multi-Agent System (MAS) approach. This model serves as a cooperative autonomy framework, facilitating interactive information exchange among different resource modules to manage complex constraints. Significantly, it models the uncertainty in ship waiting times and dynamic conditions, thus enhancing the feasibility and practicality of the proposed optimization solutions under real-world ocean environments.

c. The introduction of a novel solution framework that synergises Genetic Algorithms (GA) with the simulation model in an iterative process. This framework seeks the optimal allocation of auxiliary resources and ship autonomous scheduling under fixed capacities of anchorage, channels, and berths. It achieves multi-objective optimization of resources and autonomous scheduling in port traffic organisation, thereby presenting new perspectives and methodologies for intelligent port management.

The research methodology employed in this study is depicted in Fig. 1. The subsequent sections are organized as follows: Section 2 highlights the most recent research gaps in related fields, Section 3 describes the optimization problem associated with seaport organisation, Section 4 presents a solution approach based on simulation modelling and Genetic Algorithms (GA), Section 5 applies the model to Tianjin Port for empirical validation, and Section 6 discusses the model and proposes directions for future research.

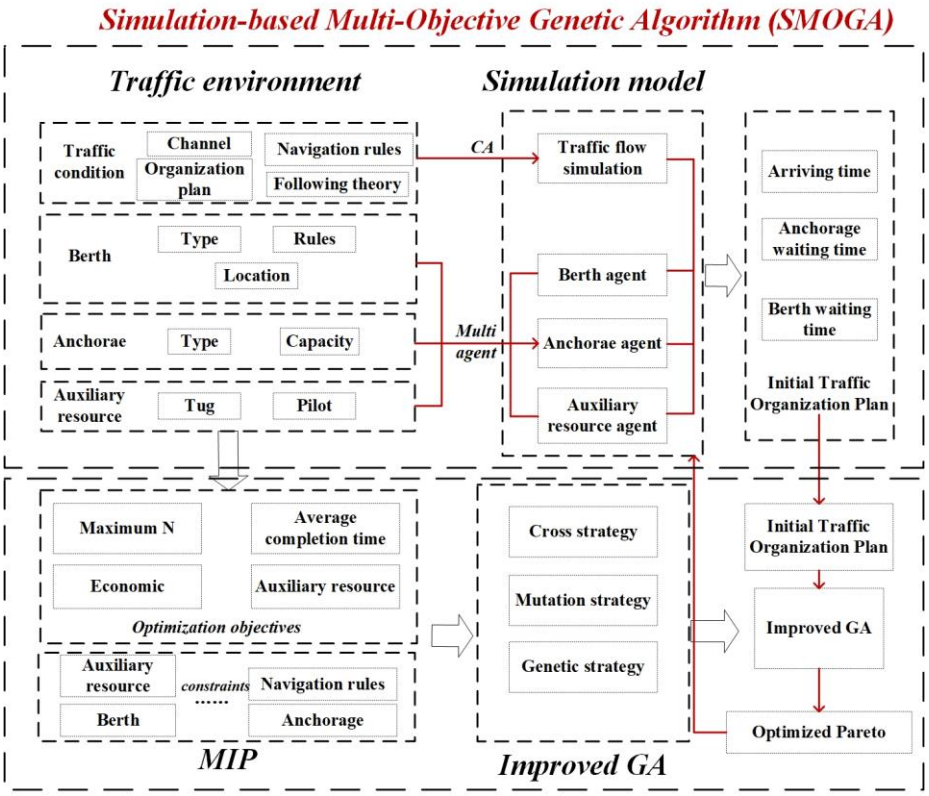


Fig. 1. Logical structure of the study

2. Literature Review

The present paper integrates heuristic optimization algorithms with traffic simulation models to address the multi-objective optimization problem of auxiliary resource allocation and ship scheduling in port traffic systems. The review section is organized into three parts: traffic organisation optimization, traffic simulation models regarding heterogeneous flows, and multi-source information fusion in the context of maritime IoT.

2.1 Traffic organisation optimization problem of port navigation system

Current studies on ship traffic organisation in ports extend beyond basic operations to specific domains such as ship route optimization (W. Chen et al., 2023; Karimi et al., 2025; M. Li et al., 2022; Norstad et al., 2011; Zhen et al., 2020), Ship speed optimization (Luo et al., 2024; Psaraftis and Kontovas, 2014; Wang et al., 2018), sea-rail intermodal transportation(Fan et al., 2019), berth allocation problem(Hsu, 2016), and Port State Control (PSC) inspection optimization (Yan et al., 2024; Yang et al., 2024), current studies on ship traffic organisation in ports mainly concentrate on tugboat resources, pilot resources, ship collision avoidance and ship scheduling arrangements (Ma et al., 2024; Sun et al., 2025; Wang et al., 2024).

Initially, scholars explored various methodological approaches. Fagerholt (2001) addressed ship scheduling as a multiple ship pickup and delivery problem with soft time windows (m-PDPSTW). Aydogdu (2012) proposed a management-oriented solution for the Istanbul Strait considering spatial-temporal distribution. Smierzchalski (2000) focused on autonomous route selection using evolutionary algorithms, while Kawaguchi et al. (2009) introduced a ship cluster behaviour model to maximize waterway resource utilization.

Subsequently, the focus shifted towards Mixed-Integer Programming (MIP) models. Corry et al. (2019) integrated channel movement scheduling with berth allocation. Jia et al. (2022, 2020, 2019) provided MIP formulations to optimize pilot and ship costs, balancing efficiency and fairness. Kang et al. (2020) attempted to optimize container ship schedules using simulation

methods. Other significant contributions include Li et al. (2019) on minimizing berthing delays, Wei et al. (2020) on tugboat scheduling, and Wu et al. (2020) on pilotage planning, demonstrating the NP-hard nature of these problems. Further advancements by Abou et al. (2021) and Liu et al. (2021b, 2021a) incorporated complex constraints like channel restrictions and one-way navigation. Recent studies have also addressed emissions via speed reduction (Xiao et al., 2021), uncertainty analysis (Ksciuka et al.,2023) and optimal control for path planning (Shu et al., 2024). With the rapid development of the electric vehicle industry, the traffic organization of roll-on/roll-off (Ro-Ro) ship liner routes carrying both electric and gasoline vehicles has also begun to attract attention (Wang et al., 2026). Despite this extensive body of work, there remains a noticeable scarcity of research specifically targeting autonomous vessel traffic organization, particularly frameworks that can dynamically adapt to the stochastic nature of future smart ports.

2.2 Port navigation system traffic simulation model

Currently, in the domain of waterway traffic, a predominant number of scholars have embarked on developing simulation models based on CA. Liu et al. (2010), utilizing diverse ship categories, safety distances, ship arrival patterns, and berth service levels, developed a CA model to simulate port waterway traffic flows. This model adeptly navigated the complexities and non-linear challenges associated with simulation. Following this, various researchers have incorporated random variables into the CA framework to simulate ship traffic flows. This integration aims to capture the impact of environmental factors on maritime movements, as outlined in studies by Qi et al. (2017; Zhen et al., 2017) and Qu et al. (2012). With increased activity in the approach channels, investigations into the effects of lane switching on traffic efficiency have been undertaken, as demonstrated in research by Sun et al. (2015), Hu et al. (2017), and Qi et al. (2021), Chen et al. (2023) and others established a ship traffic flow simulation model for narrow channels under the premise of considering navigation rules.

Concurrently, the application of multi-agent simulation technology (Zhang et al., 2005) in the field of transportation has been rapidly evolving. With the demand for higher precision, Multi-Agent Systems (MAS) have been integrated with CA. Jiang et al. (2019) combined CA with MAS to explore ship behaviour impacts on port operations, and Liu et al. (2021) applied this paradigm to LNG carrier movements.

Regarding heterogeneous traffic flow, extensive research exists in road transportation (Fan et al., 2025; Jin et al., 2025; L. Li et al., 2022; Yao et al., 2023). However, in the maritime domain, research on the coexistence of autonomous and manned vessels is emerging. Notably, Liu et al. (2024a, 2024b) developed a heterogeneous traffic flow simulation model based on CA, providing a foundation for analysing the interaction between autonomous and conventional ships in port waters.

2.3 Multi-Source Information Fusion (MSIF) and Maritime IoT

As port management evolves towards intelligence, the integration of the Internet of Things (IoT) and Multi-Source Information Fusion (MSIF) has become critical for top-level smart port design. Recent literature highlights how fusing diverse data streams enhances situational awareness and decision-making.

Liu et al. (2022a) proposed an edge computing method based on multi-source information fusion to serve autonomous vessels within the Maritime IoT (MIoT) framework. Similarly, Xiao et al. (2023) developed a trajectory prediction neural network driven by multi-source data fusion for intelligent traffic systems. Specific applications of deep learning in this context include ship trajectory prediction for port management (Liu et al., 2022b), and ship speed interval prediction under MIoT (Liu et al., 2025). Furthermore, to enhance visual

perception in smart ports, Lu et al. (2023; 2024; 2022) proposed a series of deep learning-based image enhancement methods. Complementing these analytical tools, Liang et al. (2025) introduced a rapid visualization method for massive data in MIoT. These studies collectively demonstrate the growing importance of fusing AIS data, visual data, and sensor inputs; however, the application of MSIF specifically for optimizing traffic scheduling logic remains underexplored.

2.3 Research gap

An analysis of existing research reveals three primary areas necessitating refinement: a. Integration of MSIF in Scheduling: While MSIF is widely used for prediction and perception (as discussed in Section 2.3), it is rarely directly integrated into the optimization loop of traffic organization algorithms. b. Autonomous Organization: Existing MIP models (Section 2.1) typically rely on centralized, static planning and lack the adaptive mechanisms required for autonomous vessel traffic organization. c. Simulation as an Optimizer: While simulation models (Section 2.2) effectively mimic heterogeneous flows, they are often used for evaluation rather than as an active component of the optimization process.

3. Problem description

The optimization problem of traffic organisation within port navigation systems may be characterised as a quintessential multi-objective, MIP problem. This section introduces, respectively, the process of traffic organisation and the optimization challenges inherent in port navigation systems, culminating in a multi-objective, mixed-integer programming model.

3.1 Traffic organisation

In this study, we meticulously examine the complete process of ship entry and departure from ports, focusing primarily on nautical aspects. The port resources involved in this process encompass anchorages, inbound and outbound channels, and berths, supplemented by auxiliary resources such as pilots and tugboats, in addition to shore-based support personnel. The detailed process for ship port entry and departure is as follows:

a. Ships first arrive at the anchorage, awaiting the availability of free berths as well as pilot and tugboat resources. The resource occupancy is contingent on the ship type, and upon satisfaction of these resource requirements, ships proceed to the inbound channel.

b. During the navigation phase within the inbound channel, ship speed is dependent on the type of ship and must also account for interactions with preceding and following ships.

c. Upon reaching the berth, cargo loading and unloading operations commence, the duration of which varies with the ship type. Similarly, for departure, the availability of sufficient free auxiliary resources is considered before ships embark on the outbound channel.

d. The outbound navigation process mirrors that of the inbound phase.

f. The waiting time of ships is affected by random factors: the availability of pilot/tug resources follows an exponential distribution, and the passage time of the channel is affected by the interaction of ships.

To clarify the terminology used throughout this framework, we define the hierarchical relationship as follows: “Traffic Organization” refers to the holistic management strategy for the entire port ecosystem, including rule formulation and resource coordination. “Scheduling” denotes the specific, tactical execution of this strategy, manifesting as the precise temporal assignment of vessels to channels, anchorages, and berths. The proposed framework utilizes autonomous scheduling to achieve efficient traffic organization. To formulate the intelligent traffic organization problem, this study operates under the hypothetical premise of a Level 4 Autonomous Port

environment. Specifically, we assume:

1. Full Connectivity: All vessels and port infrastructure are equipped with V2X (Vehicle-to-Everything) communication capabilities, enabling real-time data exchange regarding position, speed, and intent.
2. Digital Transparency: The status of auxiliary resources (pilots/tugs) and anchorages is digitized and broadcasted in real-time. These premises allow the proposed system to transition from traditional voice-based dispatching to data-driven digital scheduling.

Throughout the entire port entry and departure process, numerous uncertainties exist, with the most prominent being: the indeterminacy of ship waiting times at anchorages and berths due to resource constraints, and the uncertainty in navigation time within channels owing to ship speed and interactions. These elements of uncertainty significantly compound the complexity of optimising traffic organisation in port navigation systems.

3.2. Mixed-integer programming problem

To address the issue of traffic organisation optimization in port navigation systems, we have established a MIP model. This model is meticulously structured, with clearly defined parameters tailored to encapsulate the multifaceted aspects of port traffic dynamics. The formulation of the model is as follows:

Firstly, the model incorporates a comprehensive set of parameters that represent the critical elements of port traffic (**Table 1**), such as the number and types of ships, berth allocation, arrival and departure times, and resource availability (including tugs and pilots).

The essence of Multi-Source Information Fusion lies in the dynamic mapping of heterogeneous data streams into the MIP model parameters. Specifically, real-time AIS data determines the set of ships I and their initial states (Arrival Time); the dynamic status updates of pilots and tugs directly quantify the resource capacity bounds P and G (Eq. 4-5); and environmental sensor data updates the channel capacity constraints (C_{in}, C_{out}). This fusion ensures that the mathematical constraints strictly reflect the physical reality of the port.

Table1

Parameters and Decision Variables

Category	Symbol	Description
Sets:	I	The set of all ships, indexed by $i \in I$.
	T	The set of time steps over the planning horizon, indexed by $t \in T$.
	P	The set of all pilots, indexed by $p \in P$.
	G	The set of all tugboats, indexed by $g \in G$.
Parameters:		
	n	Total number of ships.
	$\|\|P\|\|$	Total number of available pilots.
	$\|\|G\|\|$	Total number of available tugboats.
	A_{cap}	Maximum capacity of the anchorage (number of ships).
	B_{cap}	Maximum capacity of the berths (number of ships).
	C_{in}	Maximum capacity of the inbound channel (number of ships at the same time).
	C_{out}	Maximum capacity of the outbound channel (number of ships at the same time).
	t_c	The time required for a ship to continuously navigate the channel.

	P_i^{req}	Number of pilots required by ship i
	G_i^{req}	Number of tugboats required by ship i
	E	Economic indicators
Decision variables:		
	$x_{it}^{in} \in \{0,1\}$	A binary variable that is 1 if ship i begins entering the inbound channel at time t, and 0 otherwise.
	$x_{it}^{out} \in \{0,1\}$	A binary variable that is 1 if ship i begins entering the outbound channel at time t, and 0 otherwise.
	$y_{it} \in \{0,1\}$	A binary variable that is 1 if ship i occupies pilotage resources at time t, and 0 otherwise.
	$z_{it} \in \{0,1\}$	A binary variable that is 1 if ship i occupies tugboat resources at time t, and 0 otherwise.
	t_i^{start}	The start time of arrival at the anchorage for ship i.
	t_i^{end}	The end time of departure completion for ship i.

Secondly, constraints are formulated to reflect the physical and operational limitations within the port, such as berth capacities, waterway traffic restrictions, and resource allocation limits. The objective function of the model is designed to optimize key aspects of port operations, like minimizing total turnaround time, maximizing resource utilization, and ensuring equitable access to port facilities.

Objective 1: Maximize the number of ships that have completed the port entry and departure process within the time period T.

The objective is formulated as:

$$Maximize\ N(T) = \sum_{i=I} \sum_{t=0}^{T-t_c} x_{it}^{out} \tag{1}$$

$N(T)$: The number of ships completing their departure process within the time period T.

Objective 2: Minimize the number of auxiliary resources required. The objective is formulated as:

$$Minimize\ p_{max} = max_{t \in T} \left(\sum_{i \in I} y_{it} \cdot P_i^{req} + \sum_{i \in I} z_{it} \cdot G_i^{req} \right) \tag{2}$$

Objective 3: Minimizing economic costs for single inbound and outbound loading and unloading. The objective is formulated as:

$$Minimize\ E = w_{time} \sum_{i \in I} (t_i^{end} - t_i^{start}) + w_{tug} \sum_{i \in I} \sum_{t \in T} (z_{it} \cdot G_i^{req}) \tag{3}$$

The weight coefficients w_{time} and w_{tug} were determined based on the actual operational cost data from Tianjin Port. Specifically, they represent the relative monetary value of vessel charter rates per hour versus the hourly service fees for tugboats, ensuring the optimization objective aligns with real-world economic priorities

Subject To：

$$\sum_{i \in I} y_{it} \cdot P_i^{req} \leq \|P\|, \forall t \in T \tag{4}$$

$$\sum_{i \in I} z_{it} \cdot G_i^{req} \leq \|G\|, \forall t \in T \tag{5}$$

$$\sum_{i \in I} (\text{ship } i \text{ is at anchorage at time } t) \leq A_{cap}, \forall t \in T \tag{6}$$

$$\sum_{i \in I} (\text{ship } i \text{ is at berth at time } t) \leq B_{cap}, \forall t \in T \tag{7}$$

$$\sum_{i \in I} \sum_{k=0}^{t_c-1} x_{i,t-k}^{in} \leq C_{in}, \forall t \in T \tag{8}$$

$$\sum_{i \in I} \sum_{k=0}^{t_c-1} x_{i,t-k}^{out} \leq C_{out}, \forall t \in T \tag{9}$$

$$x_{it}^{\text{in}} \leq y_{i,t+k}, \quad \forall i \in I, \forall t \in T, k = 0, \dots, t_c - 1 \tag{10}$$

$$x_{it}^{\text{in}} \leq z_{i,t+k}, \quad \forall i \in I, \forall t \in T, k = 0, \dots, t_c - 1 \tag{11}$$

$$x_{it}^{\text{out}} \leq y_{i,t+k}, \quad \forall i \in I, \forall t \in T, k = 0, \dots, t_c - 1 \tag{12}$$

$$x_{it}^{\text{out}} \leq z_{i,t+k}, \quad \forall i \in I, \forall t \in T, k = 0, \dots, t_c - 1 \tag{13}$$

Where: w_{time} is the cost coefficient for vessel turnaround time, w_{tug} is the cost coefficient for tugboat resource time.

Auxiliary Resource Constraints (Eq. 4 & 5): These constraints ensure that at any given time t, the total number of pilots and tugboats in use by all ships does not exceed the total number of available pilots and tugboats, respectively.

Capacity Constraints (Eq. 6 to 9): These constraints impose capacity limits on the port's key infrastructure, including the anchorage, berths, inbound channel, and outbound channel, by defining the maximum number of ships that each can accommodate at any given moment.

Resource Allocation Logic (Eq. 10 to 13): These are critical logical constraints that link a ship's transit decision to resource utilization. They stipulate that if a ship is scheduled to begin an inbound or outbound transit at time t, the required pilot and tugboat resources must be continuously allocated to that ship for the entire duration of the transit (t_c).

Lastly, the model is solved using a combination of simulation and heuristic algorithms, allowing for an efficient and practical approach to managing the complexities of port traffic organisation.

4. Solution approach

This study employs a SMOGA method which integrates simulation with GA to optimize traffic organisation schemes. It establishes a port navigation system based on CA and MAS. The fitness of multiple optimization objectives in the GA is calculated through simulation. Simultaneously, by setting simulation rules, constraints on various resources are effectively implemented. This approach also allows for the handling of uncertainties in decision variables.

4.1 Port navigation simulation model

As illustrated in **Fig. 2**, the enhanced simulation model is built upon a dual-layer architecture comprising a physical layer and a logic layer. The **physical layer** represents the tangible components of the port navigation system, including berths, anchorages, channels, and auxiliary pilot and tug services. The **logic layer** governs ship motion through two primary mechanisms: CA update rules for navigation and Multi-Agent information interaction for resource management. Within this logic layer, intelligent agents are assigned to key infrastructure such as anchorages and berths. These agents dynamically monitor and record the occupancy status of their respective components based on real-time operational conditions. Crucially, this agent-based system serves as the practical enforcement mechanism for the conceptual capacity constraints defined in the MIP model as **Eq. (6) and Eq. (7)**. By dynamically approving or denying ship entry requests based on

available capacity, the agents ensure these physical limits are strictly observed at the simulation level. This layer also incorporates a dedicated module to precisely control the deployment of auxiliary pilot and tug resources. By integrating these control strategies (multi-agent) with time-spatial discretization (CA), this dual-layer approach provides a comprehensive model of the port's navigational ecosystem, enabling more effective traffic management and optimization.

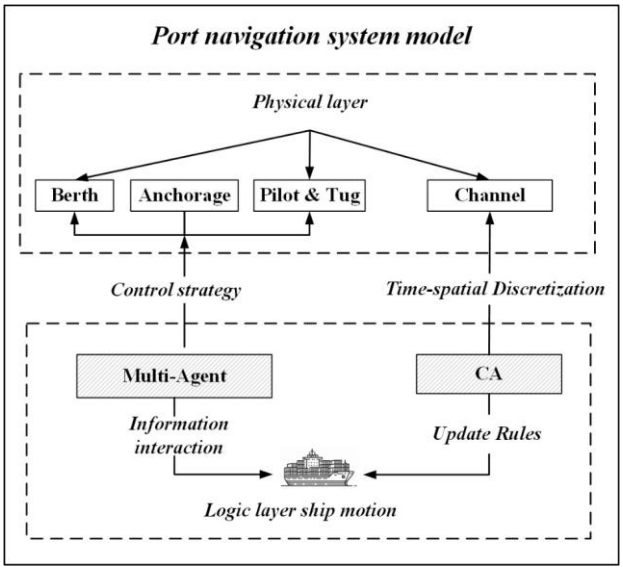


Fig. 2. Structure of simulation model

Table 2

Simulation model parameter settings

Indices	
S	All ships.
s_i	Ship i.
$pos(s_i)$	Position of $s_i$represented as grid coordinates（x, y）.
$S(s_i)$	Status of s_i , include ANCHORAGE, IN_CHANNEL, BERTH, OUT_CHANNEL, COMPLETED.
$type(s_i)$	Type of s_i, $i = 1,2,3, \cdots n$.
$res(s_i)$	The resources occupied by s_i, including the number of pilots and tugboats.
C_{space}	The size of the cellular space, $(width, heigth)$.
V	Mapping of ship type to speed, such as $V[type1] = 2, V[type2] = 1$.

1) Acceleration

Let a be the acceleration and v_t be the velocity at time t, $pos_t(s_i) = (x_t, y_t)$ be the position of ship s_i at time t. Then the calculation of acceleration can be expressed as Eq. (14).

$$v_{t+1}(s_i) = v_t(s_i) + a \tag{14}$$

2) Deceleration/Collision Avoidance

If another ship or obstacle is detected ahead, slow down or stop to avoid a collision. Assuming d is the distance between the two ships and v_t is the current speed, the deceleration can be expressed as Eq. (15).

$$v_{t+1}(s_i) = \begin{cases} 0 & \text{if } d \leq \text{safety distance} \\ v_t(s_i) & \text{otherwise} \end{cases} \tag{15}$$

3) Position Update

Let (x_t, y_t) be the position at time t, and v_t be the velocity. Position updates can be calculated based on Eq. (16).

$$pos_{t+1}(s_i) = (x_t, y_t + v_{t+1}(s_i)) \tag{16}$$

4) Resource Control

R is the total number of resources, depending on G and P, The occupation of resources can be expressed by Eq. (17).

$$R_{t+1} = R_t - r_{required} \text{ if } R_t \geq r_{required} \tag{17}$$

Resource release can be expressed in Eq. (18).

$$R_{t+1} = R_t + r_{released} \tag{18}$$

5) Status Update

The state transitions for ships in the simulation model follow the rules below. The symbols for the transition conditions are defined as follows:

C_1: A berth has been assigned to the ship.

C_2: The required auxiliary resources (pilots, tugs) for the transit are available.

C_3: The ship has reached its assigned berth position.

C_4: The ship's port service is complete.

C_5: The ship has left the designated port waterway area.

a. From ANCHORAGE to IN_CHANNEL (from anchorage to inbound channel)

$$S_{t+1}(s_i) = \begin{cases} \text{IN\_CHANNEL}, & \text{if } S_t(s_i) = \text{ANCHORAGE} \wedge C_1 \wedge C_2 \\ S_t(s_i) & \text{otherwise} \end{cases} \tag{19}$$

b. From IN_CHANNEL to BERTH (from inbound channel to berth):

$$S_{t+1}(s_i) = \begin{cases} \text{BERTH}, & \text{if } S_t(s_i) = \text{IN\_CHANNEL} \wedge C_3 \\ S_t(s_i) & \text{otherwise} \end{cases} \tag{20}$$

c. From BERTH to OUT_CHANNEL (from berth to outbound channel):

$$S_{t+1}(s_i) = \begin{cases} \text{OUT\_CHANNEL}, & \text{if } S_t(s_i) = \text{BERTH} \wedge C_4 \wedge C_2 \\ S_t(s_i) & \text{otherwise} \end{cases} \tag{21}$$

d. From OUT_CHANNEL to COMPLETED (from outbound channel to completed status):

$$S_{t+1}(s_i) = \begin{cases} \text{COMPLETED} & \text{if } S_t(s_i) = \text{OUT\_CHANNEL} \wedge C_5 \\ S_t(s_i) & \text{otherwise} \end{cases} \tag{22}$$

In the optimization of traffic organisation of the port navigation system, there are uncertainties in the transformation of ship status and ship navigation. The resource control and ship status conversion in the study are controlled by a MAS. The uncertainty in traffic organisation optimization can be expressed as Eq. (23):

$$S_{t+1} = f(S_t, X_t, R_t, M_t), where\ M_t \sim \mathcal{N}(0, \sigma^2) \tag{23}$$

S_t is the ship state at time t.

X_t is the port resource availability at time t, such as berths and channels.

R_t is the availability of auxiliary resources at time t, such as tugs, pilots.

M_t is a random variable, representing uncertainty factors, such as changes in ship motion, etc.

In this study, the movement of ships is governed by the fundamental rules of CA (Eq. 14-16), while their interactions are managed in real-time by the multi-agent module. To explicitly model the "Local Interaction" and "Cooperative Autonomy" of the system, specific communication logics are integrated:

1. Collision Avoidance (Micro-level): Based on Eq. (15), when a following ship detects that the distance to the preceding ship is less than the safety threshold, it autonomously triggers a deceleration mechanism. This simulates the localized perception-reaction loop essential for autonomous navigation.

2. Resource Negotiation (Macro-level): Unlike static scheduling where conflicts lead to infeasible solutions, the MAS possesses adaptive self-correction capabilities. When a ship requests entry, the Berth and Channel Agents autonomously evaluate real-time capacity (Eq. 6-9). If

resources are fully occupied or stochastic disruptions occur (Eq. 23), the agents execute a "Refusal-and-Wait" logic: they deny the request (Eq. 17) and return a "Wait" signal, compelling the Ship Agent to autonomously transition to the anchorage waiting state (Eq. 19). This decentralized negotiation ensures that global schedules remain robust against dynamic uncertainties without human intervention.

Furthermore, the simulation model performs a dual role beyond mere validation. Crucially, it serves as the Dynamic Fitness Evaluator within the SMOGA optimization loop. By subjecting each candidate schedule to these stochastic environmental constraints, the Digital Twin allows the optimizer to 'perceive' the non-linear impact of random disruptions, identifying robust solutions that static mathematical models would overlook.

4.2 Simulation-based Multi-Objective Genetic Algorithm (SMOGA)

Considering the fact that different types of ships have varying speeds for loading and unloading, navigation, as well as distinct auxiliary resource requirements, the sequencing of ships, along with their waiting times at berths and durations at anchorages, plays a pivotal role in influencing traffic efficiency. This study focuses on the sequencing of an array of ship types and their dwell times at different locations as key decision variables. These variables are subjected to mutation and crossover processes, with the resultant variations forming the basis of traffic organisation plans. These plans are then integrated into the simulation module, where the fitness of each plan is assessed based on the outcomes of the simulation. Resource constraints are enforced through simulation rules, and adjustments in ship status are made to effectively manage uncertainties. The optimization objectives are to **minimize** the required auxiliary resources, **maximize** the ship throughput, and **reduce** the average completion time. This approach culminates in the creation of a SMOGA framework, which incorporates simulation to address the multi-objective optimization challenges inherent in traffic organisation plans. The logic of this solution framework is depicted in **Algorithm 1**.

Algorithm 1. SMOGA for Ship Traffic Optimization

Input:

P_{size}: Size of the population
G_{max}: Number of generations for evolution
D_{sim}: Generate the initial population

Output:

$\mathcal{P}^*$: The Pareto-optimal set of solutions

Procedure:

// **Initialization**
$t \leftarrow 0$
$\mathcal{P}_0 \leftarrow \text{InitializePopulation}(D_{sim}, P_{size})$
// **Main Evolutionary Loop**
WHILE $t < G_{max}$
// **Fitness Calculation**
FOR EACH individual plan $\pi \in \mathcal{P}_t$ **DO**
$[N(\pi), p_{max}(\pi), T_{avg}(\pi)] \leftarrow Simulation(\pi)$
// Fitness vector for minimization: (-Completed Ships, Peak Resources, Avg Completion Time)
$F(\pi) \leftarrow (-N(\pi), p_{max}(\pi), T_{avg}(\pi))$
END FOR
// **Elite Selection (NSGA-II Strategy)**
$\mathcal{F} \leftarrow FastNonDominatedSort(\mathcal{P}_t)$
$\mathcal{P}_{t+1} \leftarrow \neq 0$
$i \leftarrow 1$

WHILE $|\mathcal{P}_{t+1}| + |\mathcal{F}_i| \leq P_{size}$ **DO**
  Crowding Distance Assignment $(\mathcal{F}_i)$
  $\mathcal{P}_{t+1} \leftarrow \mathcal{P}_{t+1} \cup \mathcal{F}_i$
  $i \leftarrow i + 1$
END WHILE
Sort $(\mathcal{F}_i, crowding\_distance)$
$\mathcal{P}_{t+1} \leftarrow \mathcal{P}_{t+1} \cup \mathcal{F}_i[1:(P_{size} - |\mathcal{P}_{t+1}|)]$
// **Offspring Generation**
$\mathcal{Q}_{t+1} \leftarrow Generate\ Offspring(\mathcal{P}_{t+1}, Crossover, Mutation)$
$\mathcal{P}_t = \mathcal{Q}_{t+1}$
$t \leftarrow t + 1$
END WHILE
// **Return the first Pareto front**
$\mathcal{P}^* \leftarrow FastNonDominatedSort(\mathcal{P}_t)[0]$
RETURN $\mathcal{P}^*$

1) Fitness Calculation

The calculation of fitness is a crucial step for selecting the optimal offspring within a population. In this study, the traditional mathematical approach to fitness calculation has been supplanted by a simulation-based method. This involves evaluating offspring based on the number of ships that successfully pass through, the required maximum number of p_{max}, and the average completion time, thereby allowing for a comprehensive assessment.

2) Constraints

Constraints play an important role in optimization algorithms. This research primarily incorporates two types of constraints: ship movement constraints and resource constraints. Ship movement constraints are enforced through the ship position update rules within the simulation model. Resource constraints are dynamically determined by the control modules of the MAS within the simulation model.

3) Crossover Strategy

The crossover strategy is a key operator in GA to generate new individuals, aiming to combine characteristics from two parent individuals to produce new offspring. The specific steps include:

Offspring Initialization: Two entirely independent offspring are created from two parent individuals, retaining all characteristics of the parents. This step is accomplished through deep copying to ensure that the offspring's operations do not affect the parents.

Attribute Exchange: For each ship, the algorithm searches for potential exchange candidates at the corresponding positions in the parent individuals. This search is confined to a specific range around each ship (i.e., the range of n ships ahead and behind).

The type determination and exchange logic are reflected in Formula (24): If two ships are of different types, their arrival times and anchorage waiting times are exchanged. If they are of the same type, then their berth waiting times are swapped. This step considers the characteristic differences between different types of ships and promotes genetic diversity while preserving type characteristics.

$$C_1[i], C_2[i] = \begin{cases} \text{swap}(P_1[i], P_2[i], \text{arrival\_time}, \text{anchorage\_waiting\_time}) & \text{if } P_1[i].\text{type} \neq P_2[i].\text{type} \\ \text{swap}(P_1[i], P_2[i], \text{berth\_waiting\_time}) & \text{otherwise} \end{cases} \quad (24)$$

4) Mutation Strategy

The mutation strategy in GA is a critical mechanism for introducing new characteristics and increasing population diversity. Initially, an individual is copied to avoid direct modifications to the original, ensuring the independence of the mutation operation. For each ship, a decision is

made on whether to mutate based on a pre-set mutation rate. This step ensures that the mutation is not over-applied in each generation, thereby maintaining a balance between exploration and exploitation. The minimum waiting time at the berth is determined based on the ship type, as well as the corresponding mutation value, and adjustments are made to the waiting times at anchorage and berth accordingly. Particularly for the mutation of arrival times, it is also necessary to ensure that the mutated time does not overlap with the arrival times of other ships, maintaining uniqueness in timing (as indicated in Eq. (25)).

$$\begin{aligned}&\text{data[anchorage waiting time]}\\&= max(0,\text{ship\_data[anchorage\_waiting\_time]}\\&+ \text{variation})\text{ship\_data[berth\_waiting\_time]}\\&= max(\text{berth\_waiting\_time\_min,ship\_data[berth\_waiting\_time]}\\&+ \text{variation})\end{aligned} \tag{25}$$

5. Case study

In this study, the main channel of Tianjin Port and its corresponding port area have been selected as the case study. The setting of relevant parameters is based on port information and ship AIS data, and **Fig. 3** illustrates the effect of the port space after discretization. Regarding parameter settings, consistent with the current port area of Tianjin Port's main channel, 15 berths have been established. Ship types are categorized into three classes (50,000 tons, 70,000 tons, and 100,000 tons), with speeds determined based on data extracted from AIS records. **Table 3** displays the detailed parameter settings, in which the speed strategy adopts previous related research (Liu et al., 2024b). These settings include the specific dimensions and capacities of the berths, the designated types and quantities of the ships, and the operational speeds derived from real-world navigational data. This careful calibration of parameters ensures that the simulation model closely mirrors the actual conditions and operational practices of Tianjin Port, providing a realistic and robust basis for the subsequent optimization processes. The model considers the dynamic and stochastic nature of port operations, including variations in arrival times, service durations, and the availability of key resources such as tugs and pilots.

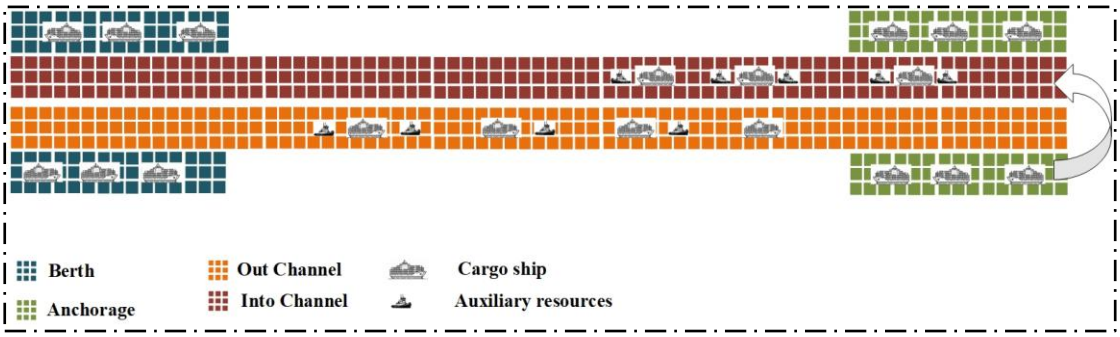


Fig. 3. Simulation space discretization diagram

Table 3
Ship parameters

Ship type	Required assistant resources	Unloading time (hour)	Speed strategy
Type 1	1	10	1
Type 2	2	15	2
Type 3	2	20	3

5.1 Validation of simulation model

An observation of the experimental results reveals a notable alignment of ship trajectories with those predicted by the CA-based traffic simulation (shown in **Fig. 4**). A key finding is that the average time taken for ships to complete their voyages gradually stabilises over time (shown in **Fig. 5**). Furthermore, the number of ships completing their entry and exit voyages from the port incrementally increases as time progresses (refer to **Fig. 6**).

This progression is corroborated by the recorded fluctuations in the time taken for each ship to complete its voyage. These fluctuations align consistently with the statistical results of the average completion time for ships, as depicted in **Fig. 7**. The Mean Absolute Error (MAE) for the average completion time stands at 1.312. Furthermore, the MAE for the number of ships completing their voyages is 1.870, indicating a strong correspondence with the actual AIS data, thereby validating the reliability of our model. The simulation results also demonstrate that the occupancy rates of each resource vary with time steps, aligning with the operational patterns of the port navigation system. This variation in resource utilisation, in tandem with the correlated data on ship completion times and numbers, provides a comprehensive insight into the dynamics of port operations (shown in **Fig. 8**). These experimental outcomes and their subsequent analysis substantiate the rationality and efficacy of the simulation model. The coherence between the observed results and the expected patterns of port traffic behaviour provides compelling evidence of the model's validity.

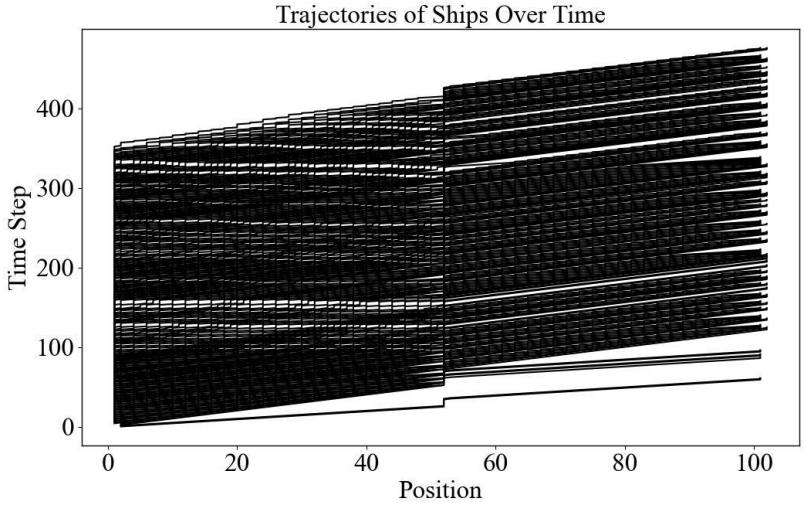


Fig. 4. Ship trajectory from simulation results

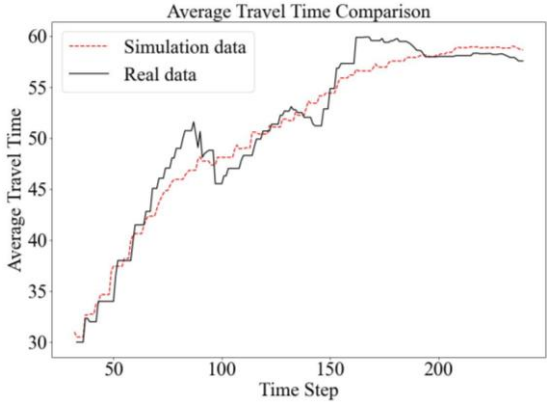


Fig. 5. Comparison of average completion

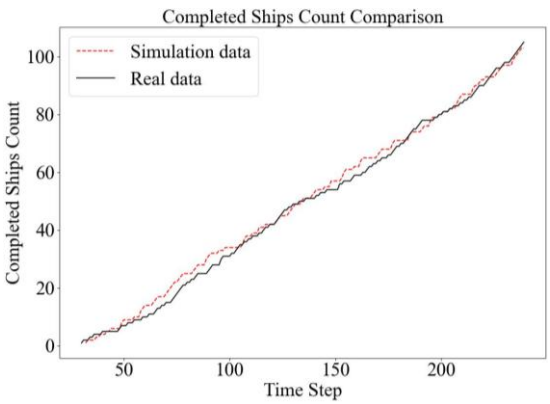


Fig. 6. Comparison of the number of

time between real data and simulated data

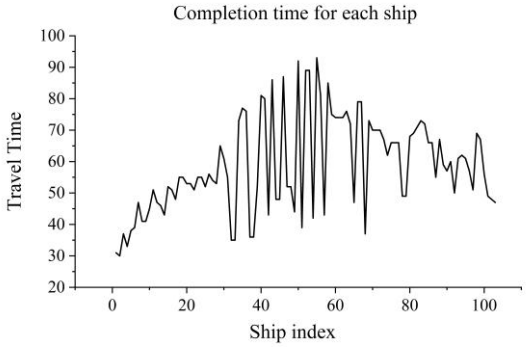


Fig. 7. Average completion time variation of simulation data

completed ships between real data and simulated data

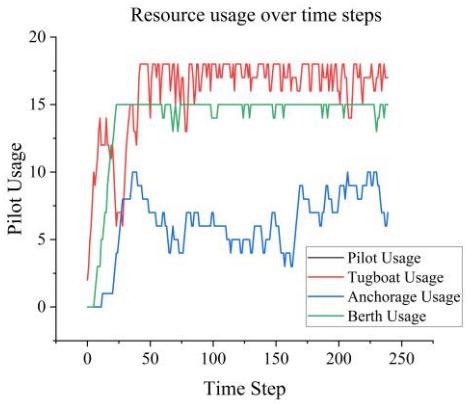


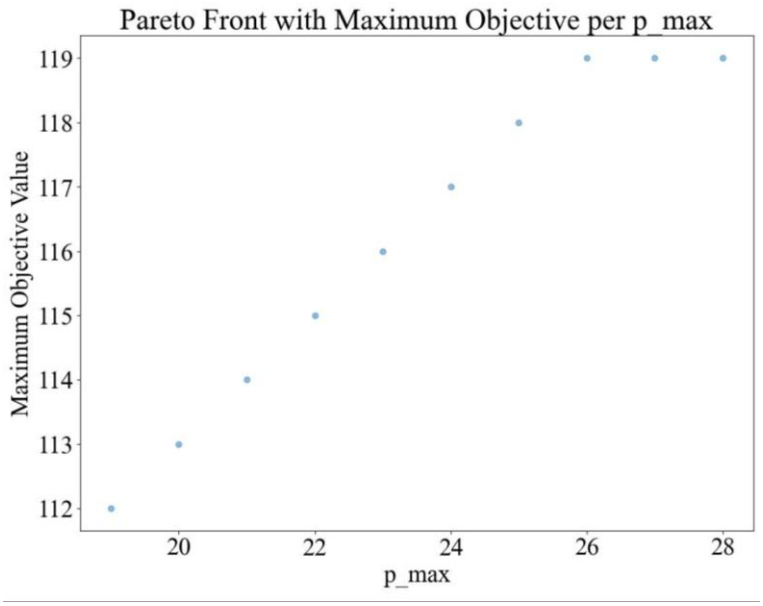
Fig. 8. Simulated port resource occupancy

5.2 Simulation-based multi-objective Genetic Algorithm (SMOGA) optimization experiment

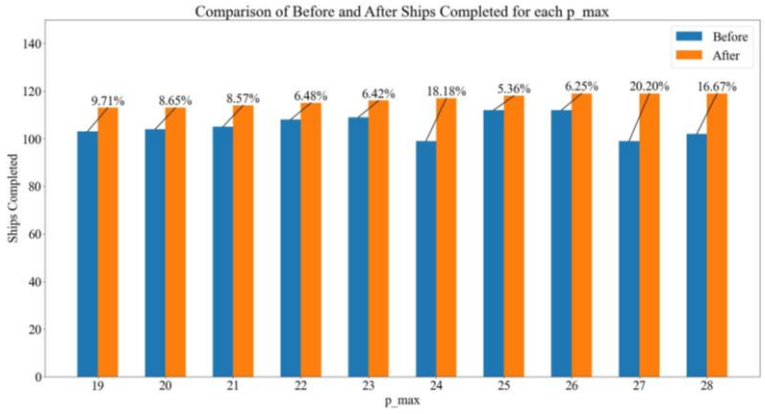
The benchmark scheme compared in this study is FCFS (First-Come, First-Served) scheduling, and resources are allocated according to demand. For heuristic optimization algorithms, each additional optimization objective adds to the computational difficulty and slows down the search for optimal solutions. Therefore, three multi-objective optimization problems were designed in this study. The first problem aims to minimize p_{max} and $maximize\ N$, conducting multi-objective optimization to find the traffic organisation plan that achieves the maximum number of ship completions within time T under different max configurations. The second problem considers not only p_{max} and N, but also adds an objective of minimising the average completion time of ships. The first problem considers only the optimal results for the maximum number of completed ships within time T in relation to p_{max}, while the second problem, in addition to considering the maximum number of ships that complete navigation, also considers the average completion time of the ships. Building upon the foundation of the previous two problems, we consider the economic indicator E during the process of ships entering and exiting ports, forming a third problem. The E is influenced by both T and p_{max}.

5.2.1 Problem 1: Optimization experiments by maximum number of ships

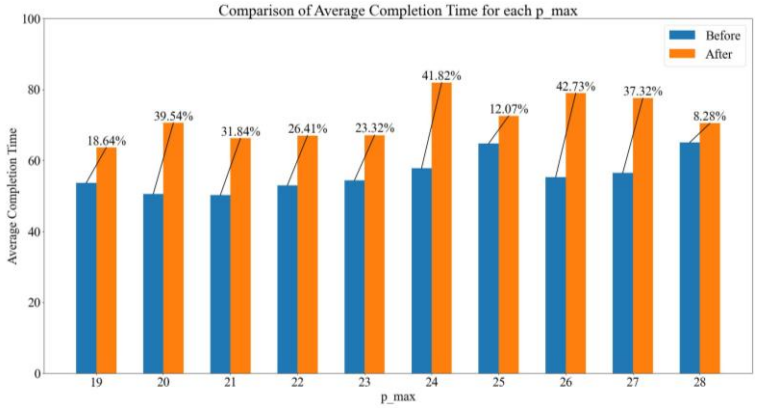
For port managers, determining the arrival time, anchoring time, time of entry into the channel, and time of departure from the berth for each ship enables effective autonomous scheduling and management. The information for all ships over a period collectively forms a set of traffic organisation plans. Using the simulation model, traffic organisation plans generated from 50 runs under pre-set parameters serve as the initial population. Each traffic organisation plan includes the ship's ID, arrival time, anchorage time, and berth waiting time. Iterative optimization is conducted on two objectives: minimizing the quantity of p_{max} and the number of ships completing navigation. The variation of optimization objectives with the number of iterations under different p_{max} is recorded, resulting in the outcomes depicted in **Fig. 9**.



(a)



(b)



(c)

Fig. 9. Experiment result for problem 1: (a) Pareto front with maximum ships completed per p_{max}, (b) Comparison of the number of completed ships before and after optimization, (c) Comparison of the average time for ships to complete their voyage before and after optimization.

The experimental results show that for **Fig. 9 (a)**, the Pareto front formed by the two optimization objectives represents traffic organisation plans optimized for each point, recording the Pareto front of the number of ships completing entry and exit from the port as auxiliary resources vary.

b. A comparison between two sets of traffic organisation plans before and after optimization clearly reveals that the number of ships completed after optimization increased by varying amounts, ranging from 5.36% to 20.20% **(Fig. 9 (b))**, while the average completion time for ships entering and leaving the port increased by 12.07% to 42.73% **(Fig. 9 (c))**.

c. It can be seen that the optimization effect is mainly reflected in reducing waiting time at the anchorage by adjusting the order of ships, thereby achieving the effect of optimizing efficiency, as illustrated in **Fig. 10**.

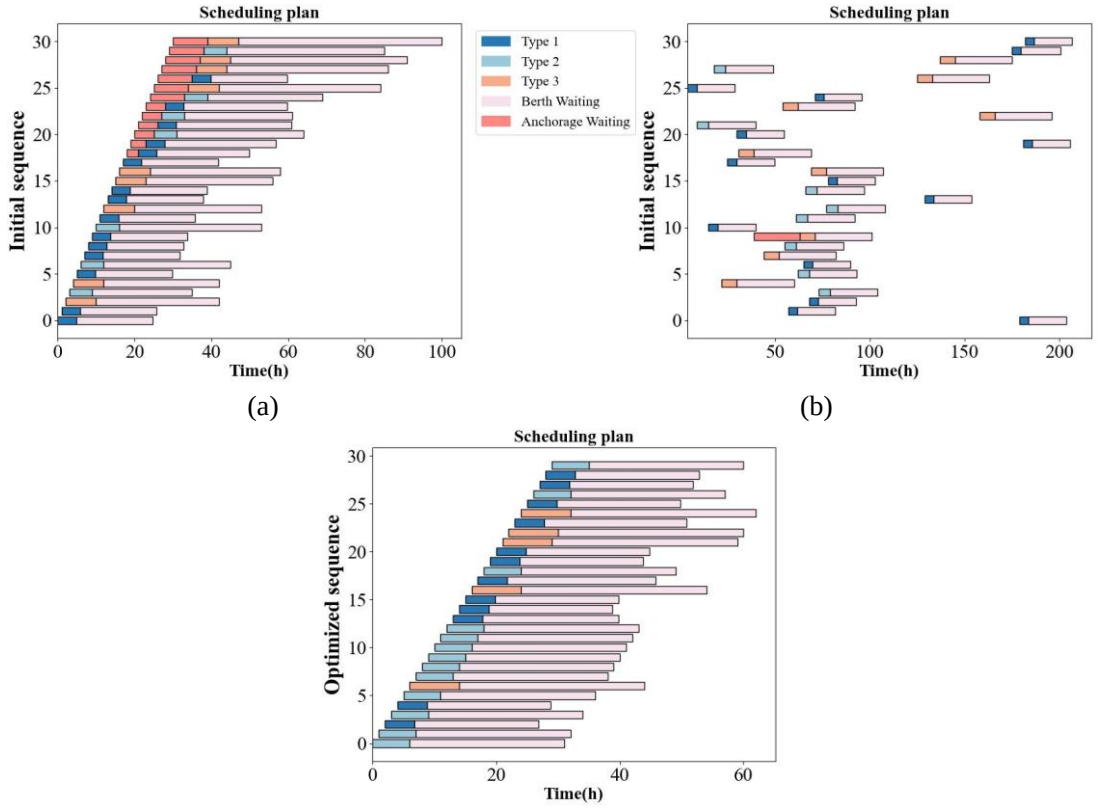
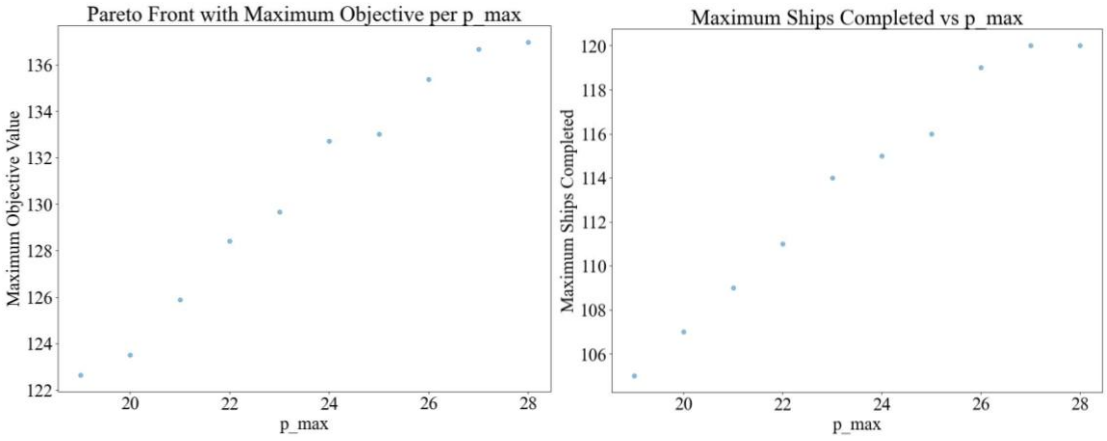


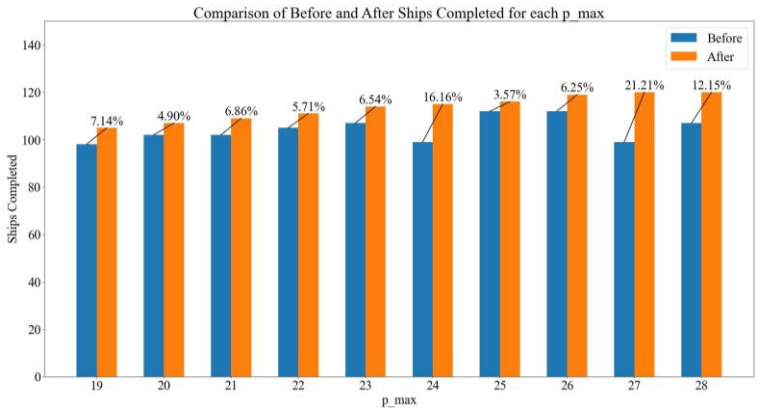
Fig. 10. Visualization of scheduling plan before and after autonomous optimization of problem 1: (a) Initial scheduling plan for the first 30 ships, (b) Optimized scheduling plan for the original first 30 ships, (c) Optimized scheduling plan for the new first 30 ships

5.2.2 Problem 2: Optimization experiments considering minimum average ship passage time and maximum number of ships

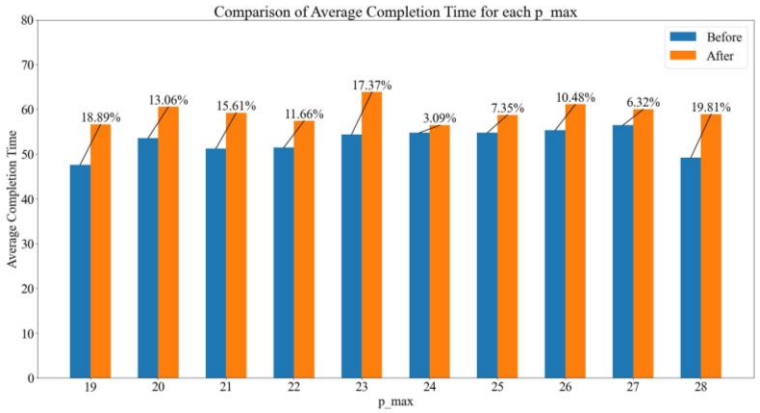
Iterative optimization was performed on the three objectives: minimizing the quantity of p_{max}, maximizing the number of ships completing navigation, and minimizing the average ship passage time. The changes in the optimization objectives under different p_{max} values were recorded throughout the iteration process. The results obtained are displayed in **Fig. 11**. These figures illustrate the trajectories of optimization progress, reflecting how the solutions evolve over time with respect to the number of auxiliary resources p_{max} and the composite objective function.



(a) (b)



(c)



(d)

Fig. 11. Experiment result for problem 2: Pareto front:(a) maximum objective per p_{max}, (b) maximum ships completed per p_{max}, Comparison: (c) the number of completed ships before and after optimization, (d) the average time for ships to complete their voyage before and after optimization

a. After incorporating consideration for the average completion time, it is observed that the optimization results still ensure that the trends of the maximum number of ships passing and the objective function remain consistent (**Fig. 11(a)**). Ultimately, it is still possible to obtain a traffic organisation plan that accommodates the maximum number of ships (**Fig. 11(b)**).

b. As the average completion time is considered, the traffic organisation plans optimized subsequently do not exhibit a significant increase in the average completion time of ships, unlike in problem 1 (**Fig. 9**).

c. It is evident that with the variation in the required maximum number of auxiliary resources p_{max}, the number of ships completed after optimization increased by 4.9% to 21.21% (**Fig. 11(c)**), but the average completion time for ships entering and leaving the port increased by only 3.09% to 19.81% (**Fig. 11(d)**).

d. It can be seen that the optimization approach and effect are the same as in problem 1, the optimization effect is mainly reflected in reducing waiting time at the anchorage by adjusting the order of ships, thereby achieving the effect of optimizing efficiency, as illustrated in **Fig. 12**.

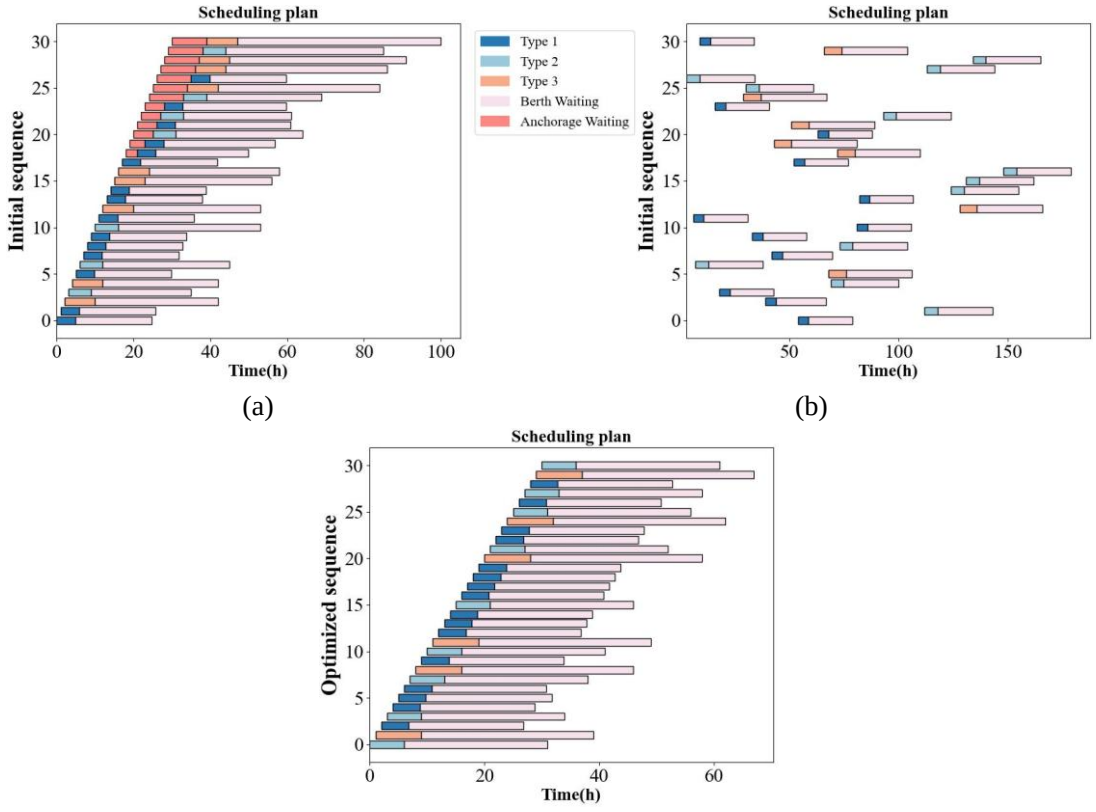
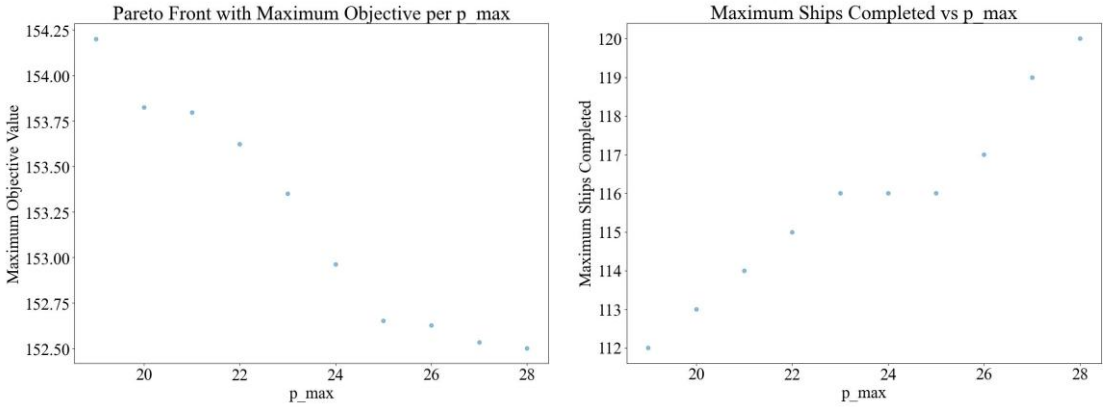


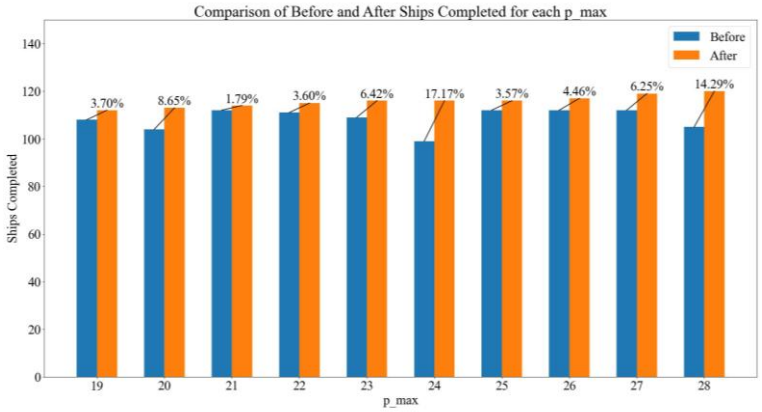
Fig. 12. Visualization of scheduling plan before and after optimization of problem 2: (a) Initial scheduling plan for the first 30 ships, (b) Optimized autonomous scheduling plan for the original first 30 ships, (c) Optimized autonomous scheduling plan for the new first 30 ships

5.2.3 Problem 3: Optimization experiments considering minimum average ship passage time, maximum number of ships and economic cost

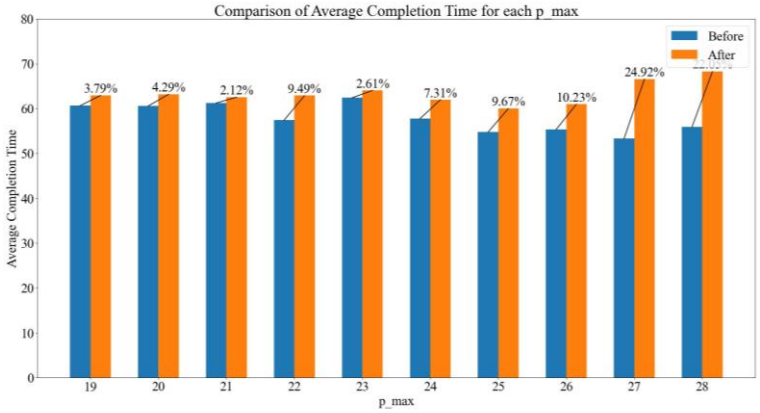
The economic efficiency of a ship during its entry and exit process is influenced by the resources used, denoted as p_{max}, and the average time taken for a single ship to complete the entry and exit. The longer the time spent on these resources, the longer the average time for entry and exit, resulting in a higher value for the economic index E, which signifies poorer economic efficiency. Therefore, after incorporating the economic efficiency index into the weighted objectives, new experimental results were obtained.



(a) (b)



(c)



(d)

Fig. 13. Experiment result for problem 3: Pareto front:(a) maximum objective per p_{max} considering economic cost, (b) maximum ships completed per p_{max} considering economic cost, Comparison: (c) the number of completed ships before and after optimization considering economic cost, (d) the average time for ships to complete their voyage before and after optimization considering economic cost

a. From **Fig. 13(a)**, it can be observed that, unlike problem 1 and problem 2, the weighted

objective value shows an inversely proportional trend with the increase of p_{max}.

b. As can be observed from **Fig. 13(b)**, the proposed algorithm framework is still able to generate traffic organisation schemes corresponding to different maximum completion ship quantities (p_{max}), even after considering economic factors. Moreover, this quantity increases with the increase of p_{max}.

c. Analysis of the results before and after optimization reveals that (**Fig. 13(c), Fig. 13(d)**), in terms of the number of ships optimized for navigation completion, there is no obvious trend for different p_{max} optimization effects. However, in terms of average completion time, as p_{max} increases, the average time for ships to complete navigation increases more significantly.

d. The experimental results indicate that after taking economic factors into account, the optimization effect is still evident. This is achieved by reordering the sequence of ships, effectively reducing the waiting time of ships at anchorages, thereby enhancing traffic efficiency, as illustrated in **Fig. 14**.

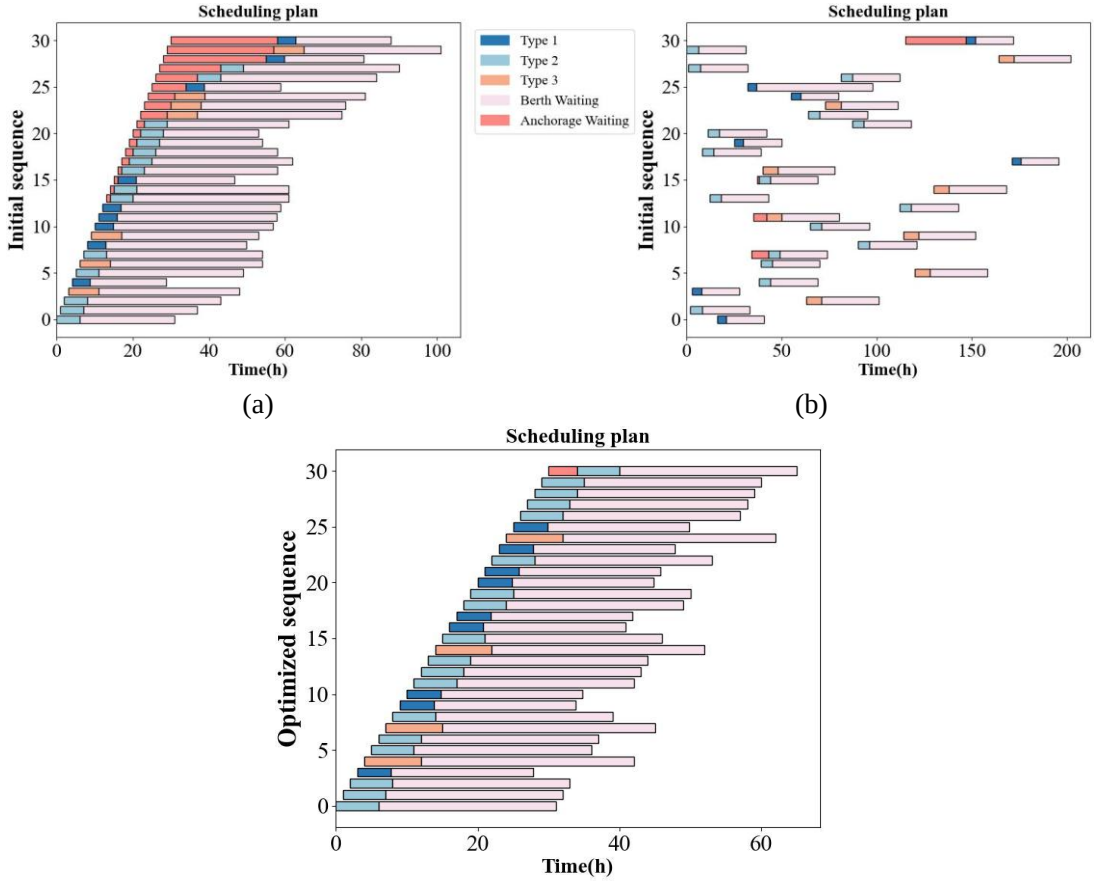


Fig. 14. Visualization of scheduling plan before and after optimization of problem 3: (a) Initial scheduling plan for the first 30 ships, (b) Optimized autonomous scheduling plan for the original first 30 ships, (c) Optimized autonomous scheduling plan for the new first 30 ships

5.3 Benchmark analysis and algorithm validating

To rigorously validate the performance of the proposed SMOGA, a comprehensive comparative study was conducted. In addition to the baseline First-Come, First-Served (FCFS) rule and standard meta-heuristics like NSGA-II and Particle Swarm Optimization (PSO), we expanded the benchmark to include Ant Colony Optimization (ACO), Simulated Annealing (SA), and the Grey Wolf Optimizer (GWO), which has demonstrated superior performance in recent

path planning studies. To ensure fair comparison, the basic parameters of all algorithms were standardized: the population size was set to 50, and the maximum number of iterations was set to 100, consistent with the proposed SMOGA algorithm. For algorithm-specific parameters (e.g., crossover/mutation rate of NSGA-II, inertia weight of PSO), we adopted common configurations and verified their convergence through preliminary tuning experiments.

All algorithms were tested across the three defined problems to evaluate their capabilities in terms of port throughput (number of completed ships) and operational efficiency (average turnaround time). The comparative results are summarized in Table 4 and visualized in Fig. 15.

Table 4. Performance comparison of SMOGA with benchmark algorithms.

Scenarios	Algorithms	Number of completed ships after optimization	Average time for ships to complete their voyage after optimization
Problem 1	FCFS	103	53.65
	NSGA-II	115	80.27
	PSO	110	75.34
	ACO	108	72.80
	SA	110	74.37
	GWO	111	77.92
	SMOGA	119	70.47
Problem 2:	FCFS	103	53.65
	NSGA-II	116	66.78
	PSO	111	65.33
	ACO	108	60.62
	SA	112	73.63
	GWO	113	74.18
	SMOGA	120	58.94
Problem 3	FCFS	103	53.65
	NSGA-II	115	78.36
	PSO	110	74.29
	ACO	112	72.80
	SA	110	74.37
	GWO	114	76.46
	SMOGA	120	68.28

The comparative results in Table 4 and Fig. 15 demonstrate the comprehensive superiority of the proposed SMOGA framework:

1. Dominance in Throughput: SMOGA consistently achieves the highest port capacity. In Problem 2, for instance, SMOGA successfully scheduled 120 ships, significantly outperforming the best alternative meta-heuristics, GWO (113 ships) and SA (112 ships). Traditional algorithms like ACO lagged further behind (108 ships), proving that the proposed simulation-based mechanism explores the solution space more effectively than standard swarm intelligence.

2. Superior Efficiency (Strict Dominance): A striking finding from the updated data is that SMOGA is the most efficient among all optimization algorithms.

Beating the Swarm: While algorithms like GWO and ACO are often cited for their speed, in this complex constraint environment, they incurred higher average delays. For example, in Problem 2, the average completion times for ACO (60.62h) and GWO (74.18h) were notably

higher than that of SMOGA (58.94h).

The Only Outlier: The only method faster than SMOGA is the baseline FCFS (53.65h). However, this speed is deceptive, as FCFS achieves it by simply failing to schedule nearly 15% of the vessels (only 103 completed).

To provide a comprehensive evaluation beyond numerical results, Table 5 presents a qualitative comparison of the proposed SMOGA against mainstream port scheduling approaches across four key dimensions: data fusion capability, handling of stochastic randomness, support for autonomous behaviors, and computational balance.

Table 5. Qualitative comparison of different scheduling frameworks.

Feature / Framework	Rule-based (FCFS)	Traditional MIP	Standard Meta-heuristics (NSGA-II/PSO)	**Proposed SMOGA**
Multi-source Data Fusion	Low (Single source)	Medium (Static constraints)	Medium (Penalty functions)	**High (MIP + Digital Twin Integration)**
Stochastic Randomness	None (Deterministic)	Low (Hard to solve)	Medium (Requires robust optimization)	**High (Simulation-based feedback)**
Autonomous Ship Support	None	Low (Centralized only)	Low (Global planning)	**High (Agent-based Cooperative Autonomy)**
Computational Efficiency	Very High	Low (NP-hard scaling)	Medium (Slow convergence)	**Balanced (High throughput / Reasonable time)**

These results confirm that SMOGA does not merely trade off time for capacity; it improves both simultaneously compared to other intelligent algorithms. It serves as a strictly dominant solution against NSGA-II, PSO, ACO, SA, and GWO, validating that fusing high-fidelity simulation with evolutionary search is the optimal strategy for autonomous port scheduling.

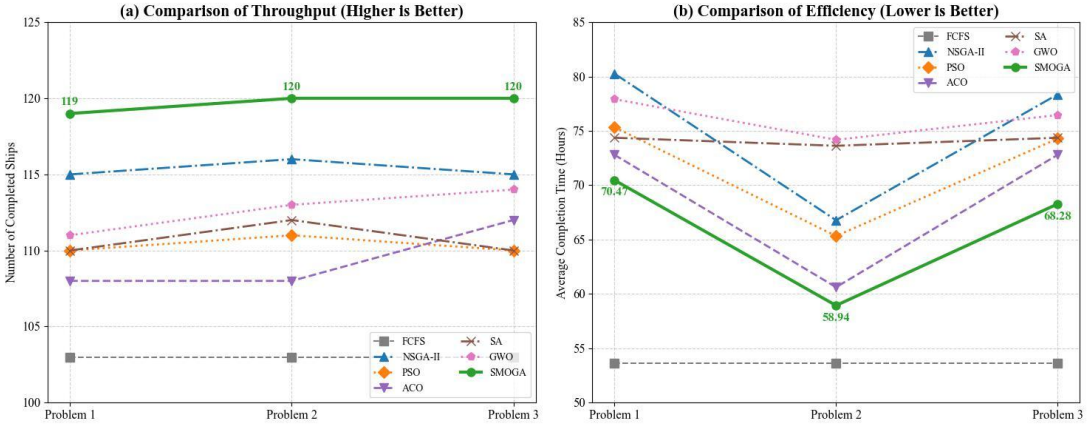


Fig. 15. Balanced result of different algorithms on three problems

5.4 Discussion

From the experimental results and comparisons in the simulation part, it is evident that our designed port navigation system simulation model is reliable and effective, closely reflecting the actual operational conditions of the port. The experimental results from the optimization part demonstrate that our framework, which integrates simulation and optimization, effectively

optimizes traffic organisation. A comparative analysis of the three problems is as follows:

Comparing problem 1 and problem 2, it is observed that focusing solely on maximizing the number of ships passing can achieve good optimization results with only a slight increase in p_{max}. However, as p_{max} continues to increase, the optimization effects of the three problems on the maximum number of ships passing are essentially the same in the end (**Fig. 16**). An analysis of the average completion time of ships under the two Problems reveals that in problem 1, which only considers the maximum number of ship completions, the metric of average completion time is overlooked. This leads to an increase in the average completion time of ships in the optimized traffic organisation plan, ranging from 18.65% to 52.72% compared to the pre-optimization plan (**Fig. 17**). However, when average completion time is considered in the optimization problem, this issue is significantly mitigated, and the increase in average completion time is reduced to 5.25%-19.05%.

By comparing the results of problem 3 with the experimental results of problem 1, it can be observed that there is no significant difference in the number of ships completed at maximum capacity (**Fig. 18**), and the trend of change is essentially the same. However, when comparing the average completion time (**Fig. 17 and 19**), it can be found that after considering economic indicators, the average completion time of ships has actually increased. Therefore, it can be inferred that blindly focusing on the efficiency of port operations may have a negative impact on economy. It is observed that due to the significant optimization potential in the arrival sequence of ships, the optimization focus is primarily on reducing waiting times at anchorages. The optimization algorithm achieves this by reordering the ships' arrival sequence to decrease the time spent waiting at anchorages. In contrast, the waiting time required at berths is subject to resource and process constraints, resulting in limited optimization potential. The experimental results demonstrate that the framework combining simulation with optimization algorithms aligns well with practical scenarios. However, the principle of fairness has been overlooked in the process of rearranging the order of ship arrival (**Fig. 10, Fig. 12 and 14**). It is worth noting that while SMOGA successfully optimizes the comprehensive objective, the average completion time in Problem 3 (considering economic cost) is slightly higher than in Problem 2 (time-only optimization). This is a calculated logical trade-off: to minimize the total Economic Cost (E), the algorithm autonomously prioritizes reducing the usage of expensive auxiliary resources (tugs/pilots) over pure speed. Consequently, some ships are scheduled to wait slightly longer for a "cheaper" time window where resource contention is lower, thereby sacrificing marginal time efficiency to achieve optimal economic viability

The "Autonomous Organization" capability of the proposed system is concretely manifested in the elimination of passive waiting times. As observed in the initial schedules **(Figs. 10a, 12a, and 14a)**, approximately 30% to 50% of vessels were compelled to wait at the anchorage due to resource contention and uncoordinated arrivals. However, the SMOGA framework autonomously re-sequenced the vessel entry order without human intervention. The impact is evident in the optimized results **(Figs. 10b, 12b, and 14b)**, where anchorage waiting times were almost completely eliminated for all ships. The only exception occurred in Scenario 3 **(Fig. 14b)**, where a single vessel retained a brief waiting period due to tight economic constraints. This drastic transition—from substantial delays to seamless transit—demonstrates the system's capacity to autonomously resolve conflicts by adjusting temporal sequences.

Regarding the system's adaptability to high dynamics, although the current 30-minute computation time precludes instantaneous collision avoidance, it is perfectly suited for Rolling Horizon Optimization (RHO) at the tactical level. In practical deployment, the framework is designed to operate on a sliding window (e.g., updating the schedule every 4 hours for the next 12-hour horizon). As new ships arrive or resources change, the Digital Twin absorbs these

deviations, and the SMOGA re-optimizes the subsequent window. This periodic re-planning ensures that the "Traffic Organization" remains robust against the stochastic nature of maritime traffic without requiring second-level latency.

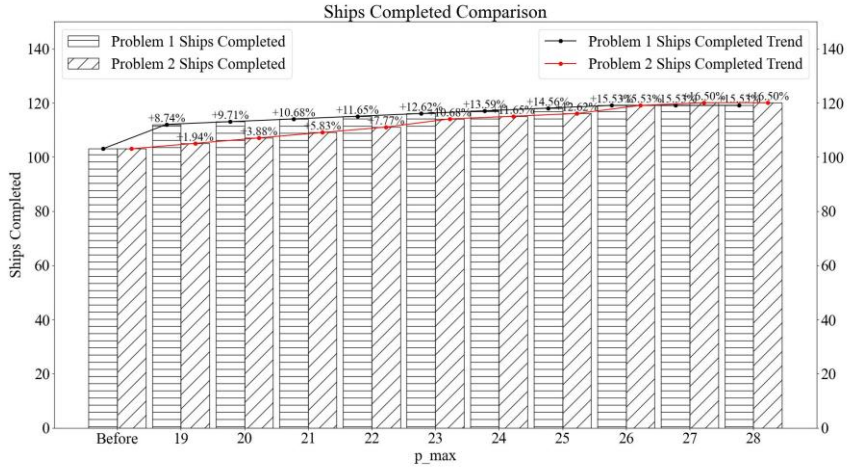


Fig. 16. Comparison of the optimization results of the number of completed ships under problem 1&2

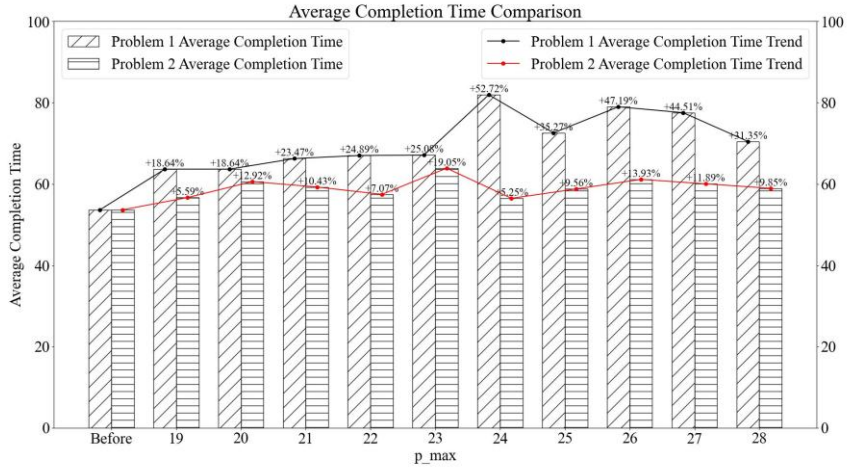


Fig. 17. Comparison of the optimization results of the average ship navigation time under problem 1&2

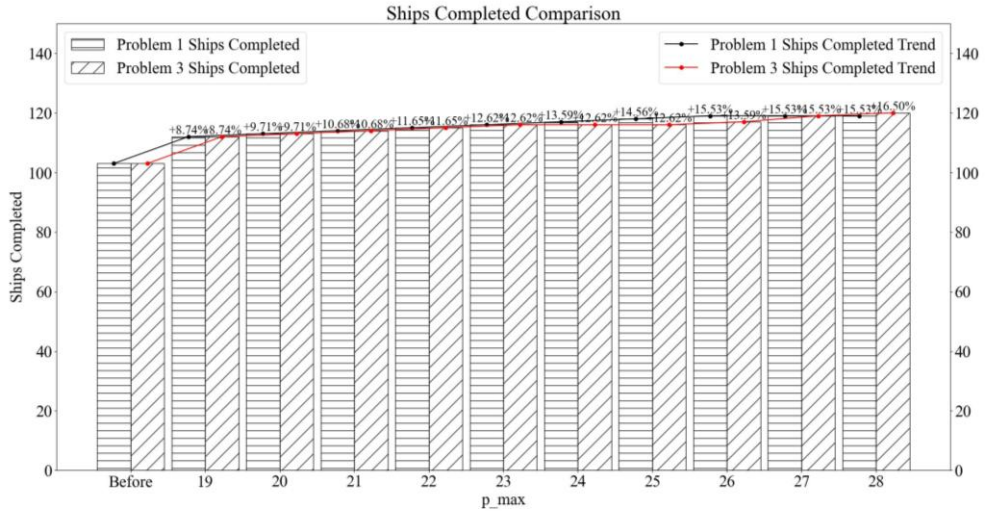


Fig. 18. Comparison of the optimization results of the number of completed ships under problem 1&3

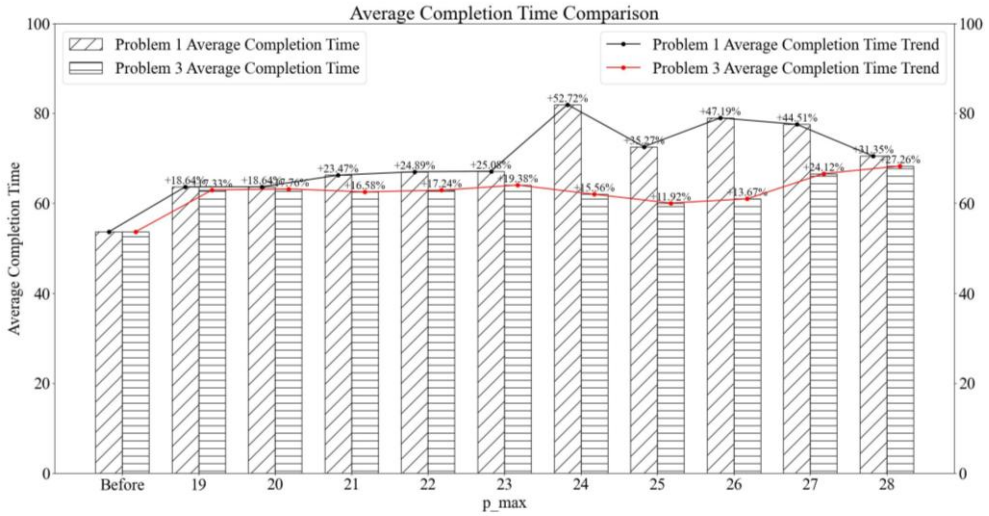


Fig. 19. Comparison of the optimization results of the number of completed ships under problem 1&3

6. Conclusion and future work

The transition towards autonomous port systems presents unique challenges that traditional static scheduling models fail to address, particularly regarding stochastic uncertainties and dynamic resource coupling. This study proposes an Intelligent Traffic Organization framework that bridges the gap between mathematical planning and dynamic execution.

By fusing a MIP formulation with a high-fidelity digital twin, the proposed framework effectively solves the “pain point” of rigid scheduling. Unlike traditional MIP models that often collapse under the unpredictability of ocean conditions, our Simulation-based Multi-Objective Genetic Algorithm (SMOGA) utilizes a cooperative autonomy mechanism. This allows for the fusion of heterogeneous data streams—from vessel trajectories to pilot availability-into a unified, robust decision space.

The experimental validation at Tianjin Port demonstrates that the proposed method significantly outperforms traditional rules and standard meta-heuristics. By shifting from static rule-based management to evolutionary autonomous optimization, the system increases throughput by 16.5% and reduces vessel turnaround time by 11.7%. This research provides a viable pathway for realizing robust, autonomous decision-making in the next generation of smart ports.

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References

Abou Kasm, O., Diabat, A., Bierlaire, M., 2021. Vessel scheduling with pilotage and tugging considerations. Transportation Research Part E: Logistics and Transportation Review 148, 102231. https://doi.org/10.1016/j.tre.2021.102231

Al-Dhaheri, N., Diabat, A., 2017. A Lagrangian relaxation-based heuristic for the multi-ship quay crane scheduling problem with ship stability constraints. Ann Oper Res 248, 1–24. https://doi.org/10.1007/s10479-016-2239-8

Aydogdu, Y.V., Yurtoren, C., Park, J.-S., Park, Y.-S., 2012. A Study on Local Traffic

Management to Improve Marine Traffic Safety in the Istanbul Strait. The Journal of Navigation 65, 99–112. https://doi.org/10.1017/S0373463311000555

Chen, L., Qi, J., Shi, J., 2023. A cellular automata ship traffic flow model considering navigation rules in narrowing channel. Alexandria Engineering Journal 69, 715–726. https://doi.org/10.1016/j.aej.2023.01.062

Chen, W., Chen, J., Geng, J., Ye, J., Yan, T., Shi, J., Xu, J., 2023. Monitoring and evaluation of ship operation congestion status at container ports based on AIS data. Ocean & Coastal Management 245, 106836. https://doi.org/10.1016/j.ocecoaman.2023.106836

Corry, P., Bierwirth, C., 2019. The Berth Allocation Problem with Channel Restrictions. Transportation Science 53, 708–727. https://doi.org/10.1287/trsc.2018.0865

Fagerholt, K., 2001. Ship scheduling with soft time windows: An optimisation based approach. European Journal of Operational Research 131, 559–571. https://doi.org/10.1016/S0377-2217(00)00098-9

Fan, Q., Jin, Y., Wang, W., Yan, X., 2019. A performance-driven multi-algorithm selection strategy for energy consumption optimization of sea-rail intermodal transportation. Swarm and Evolutionary Computation 44, 1–17. https://doi.org/10.1016/j.swevo.2018.11.007

Fan, R., Lu, J., Wang, D.Z.W., Li, M., Liu, Q., 2025. Group-benefit control strategy for connected automated vehicles in mixed traffic at intersections. Transportation Research Part C: Emerging Technologies 175, 105121. https://doi.org/10.1016/j.trc.2025.105121

Hsu, H.-P., 2016. A HPSO for solving dynamic and discrete berth allocation problem and dynamic quay crane assignment problem simultaneously. Swarm and Evolutionary Computation 27, 156–168. https://doi.org/10.1016/j.swevo.2015.11.002

Hu, H., Chen, X., Sun, Z., 2017. Effect of Water Flows on Ship Traffic in Narrow Water Channels Based on Cellular Automata. Polish Maritime Research 24. https://doi.org/10.1515/pomr-2017-0115

Jia, S., Li, C.-L., Xu, Z., 2020. A simulation optimization method for deep-sea vessel berth planning and feeder arrival scheduling at a container port. Transportation Research Part B: Methodological 142, 174–196. https://doi.org/10.1016/j.trb.2020.10.007

Jia, S., Li, C.-L., Xu, Z., 2019. Managing Navigation Channel Traffic and Anchorage Area Utilization of a Container Port. Transportation Science 53, 728–745. https://doi.org/10.1287/trsc.2018.0879

Jia, S., Meng, Q., Kuang, H., 2022. Equitable Vessel Traffic Scheduling in a Seaport. Transportation Science 56, 162–181. https://doi.org/10.1287/trsc.2021.1076

Jiang, L., Huang, G., Huang, C., Wang, W., 2019. Data Mining and Optimization of a Port Vessel Behavior Behavioral Model Under the Internet of Things. IEEE Access 7, 139970–139983. https://doi.org/10.1109/ACCESS.2019.2943654

Jin, J., Huang, H., Li, Y., Zhang, G., Dong, Y., Zhou, B., Xue, H., 2025. Variable speed limit modelling to improve traffic safety and efficiency of mixed traffic flow by a two-stage framework. Transportmetrica A: Transport Science 21, 2253476. https://doi.org/10.1080/23249935.2023.2253476

Kang, L., Meng, Q., Tan, K.C., 2020. Tugboat scheduling under ship arrival and tugging process time uncertainty. Transportation Research Part E: Logistics and Transportation Review 144,

102125. https://doi.org/10.1016/j.tre.2020.102125
Karimi, N., Javanmardi, E., Nadaffard, A., Facchini, F., 2025. Systematic analysis and optimization of operational delay factors in port supply chains using a hybrid DEMATEL-OPA-DGRA approach. Ocean & Coastal Management 263, 107620. https://doi.org/10.1016/j.ocecoaman.2025.107620
Kawaguchi, A., Inaishi, M., Kondo, H., Kondo, M., 2009. Towards the development of intelligent navigation support systems for group shipping and global marine traffic control. IET Intelligent Transport Systems 3, 257–267. https://doi.org/10.1049/iet-its.2008.0080
Ksciuk, J., Kuhlemann, S., Tierney, K., Koberstein, A., 2023. Uncertainty in maritime ship routing and scheduling: A Literature review. European Journal of Operational Research 308, 499–524. https://doi.org/10.1016/j.ejor.2022.08.006
Li, L., Wang, C., Zhang, Y., Qu, X., Li, R., Chen, Z., Ran, B., 2022. Microscopic state evolution model of mixed traffic flow based on potential field theory. Physica A: Statistical Mechanics and its Applications 607, 128185. https://doi.org/10.1016/j.physa.2022.128185
Li, M., Xie, C., Li, X., Karoonsoontawong, A., Ge, Y.-E., 2022. Robust liner ship routing and scheduling schemes under uncertain weather and ocean conditions. Transportation Research Part C: Emerging Technologies 137, 103593. https://doi.org/10.1016/j.trc.2022.103593
Li, S., Jia, S., 2019. The seaport traffic scheduling problem: Formulations and a column-row generation algorithm. Transportation Research Part B: Methodological 128, 158–184. https://doi.org/10.1016/j.trb.2019.08.003
Liang, M., Liu, K., Gao, R., Li, Y., 2025. Integrating GPU-Accelerated for Fast Large-Scale Vessel Trajectories Visualization in Maritime IoT Systems. IEEE Transactions on Intelligent Transportation Systems 26, 4048–4065. https://doi.org/10.1109/TITS.2024.3521050
Liu, B., Li, Z.-C., Sheng, D., Wang, Y., 2021a. Integrated planning of berth allocation and vessel sequencing in a seaport with one-way navigation channel. Transportation Research Part B: Methodological 143, 23–47. https://doi.org/10.1016/j.trb.2020.10.010
Liu, B., Li, Z.-C., Wang, Y., Sheng, D., 2021b. Short-term berth planning and ship scheduling for a busy seaport with channel restrictions. Transportation Research Part E: Logistics and Transportation Review 154, 102467. https://doi.org/10.1016/j.tre.2021.102467
Liu, J., Liu, Y., Qi, L., 2021. Modelling liquefied natural gas ship traffic in port based on cellular automaton and multi-agent system. The Journal of Navigation 74, 533–548. https://doi.org/10.1017/S0373463321000059
Liu, J., Zhou, F., Wang, M., 2010. Simulation of Waterway Traffic Flow at Harbor Based on the Ship Behavior and Cellular Automata, in: 2010 International Conference on Artificial Intelligence and Computational Intelligence. Presented at the 2010 International Conference on Artificial Intelligence and Computational Intelligence, pp. 542–546. https://doi.org/10.1109/AICI.2010.352
Liu, R.W., Guo, Y., Lu, Y., Chui, K.T., Gupta, B.B., 2023. Deep Network-Enabled Haze Visibility Enhancement for Visual IoT-Driven Intelligent Transportation Systems. IEEE Transactions on Industrial Informatics 19, 1581–1591. https://doi.org/10.1109/TII.2022.3170594
Liu, R.W., Guo, Y., Nie, J., Hu, Q., Xiong, Z., Yu, H., Guizani, M., 2022a. Intelligent

Edge-Enabled Efficient Multi-Source Data Fusion for Autonomous Surface Vehicles in Maritime Internet of Things. IEEE Transactions on Green Communications and Networking 6, 1574–1587. https://doi.org/10.1109/TGCN.2022.3158004

Liu, R.W., Liang, M., Nie, J., Lim, W.Y.B., Zhang, Y., Guizani, M., 2022b. Deep Learning-Powered Vessel Trajectory Prediction for Improving Smart Traffic Services in Maritime Internet of Things. IEEE Transactions on Network Science and Engineering 9, 3080–3094. https://doi.org/10.1109/TNSE.2022.3140529

Liu, Yang, Liu, J., Liu, Yi, Zhang, Q., Shu, J., Zhang, Y., 2024a. Simulation modelling and analysis of linkage-controlled traffic scheme in waterway transport key nodes. Simulation Modelling Practice and Theory 102958. https://doi.org/10.1016/j.simpat.2024.102958

Liu, Yang, Liu, J., Zhang, Q., Liu, Yi, Wang, Y., 2024b. Effect of dynamic safety distance of heterogeneous traffic flows on ship traffic efficiency: A prediction and simulation approach. Ocean Engineering 294, 116660. https://doi.org/10.1016/j.oceaneng.2023.116660

Liu, Yang, Liu, J., Zhang, Q., Liu, Yi, Wang, Y., Yang, L., 2025. Maritime IoT-oriented ship speed prediction: Integrating adaptive wavelet analysis and attention-based uncertainty modelling. Regional Studies in Marine Science 91, 104574. https://doi.org/10.1016/j.rsma.2025.104574

Lu, Y., Guo, Y., Liu, R.W., Ren, W., 2022. MTRBNet: Multi-Branch Topology Residual Block-Based Network for Low-Light Enhancement. IEEE Signal Processing Letters 29, 1127–1131. https://doi.org/10.1109/LSP.2022.3162145

Lu, Y., Yang, D., Gao, Y., Liu, R.W., Liu, J., Guo, Y., 2024. AoSRNet: All-in-One Scene Recovery Networks via multi-knowledge integration. Knowledge-Based Systems 294, 111786. https://doi.org/10.1016/j.knosys.2024.111786

Luo, X., Yan, R., Wang, S., 2024. Ship sailing speed optimization considering dynamic meteorological conditions. Transportation Research Part C: Emerging Technologies 167, 104827. https://doi.org/10.1016/j.trc.2024.104827

Ma, Q., Tang, H., Liu, C., Zhang, M., Zhang, D., Liu, Z., Zhang, L., 2024. A big data analytics method for the evaluation of maritime traffic safety using automatic identification system data. Ocean & Coastal Management 251, 107077. https://doi.org/10.1016/j.ocecoaman.2024.107077

Norstad, I., Fagerholt, K., Laporte, G., 2011. Tramp ship routing and scheduling with speed optimization. Transportation Research Part C: Emerging Technologies, Freight Transportation and Logistics (selected papers from ODYSSEUS 2009 - the 4th International Workshop on Freight Transportation and Logistics) 19, 853–865. https://doi.org/10.1016/j.trc.2010.05.001

Psaraftis, H.N., Kontovas, C.A., 2014. Ship speed optimization: Concepts, models and combined speed-routing scenarios. Transportation Research Part C: Emerging Technologies 44, 52–69. https://doi.org/10.1016/j.trc.2014.03.001

Qi, L., Ji, Y., Balling, R., Xu, W., 2021. A cellular automaton-based model of ship traffic flow in busy waterways. The Journal of Navigation 74, 605–618. https://doi.org/10.1017/S0373463320000636

Qi, L., Zheng, Z., Gang, L., 2017. A cellular automaton model for ship traffic flow in waterways.

Physica A: Statistical Mechanics and its Applications 471, 705–717. https://doi.org/10.1016/j.physa.2016.12.028

Qu, X., Meng, Q., 2012. The economic importance of the Straits of Malacca and Singapore: An extreme-scenario analysis. Transportation Research Part E: Logistics and Transportation Review, Select Papers from the 19th International Symposium on Transportation and Traffic Theory 48, 258–265. https://doi.org/10.1016/j.tre.2011.08.005

Shu, Y., Xiong, C., Zhu, Y., Liu, K., Liu, R.W., Xu, F., Gan, L., Zhang, L., 2024. Reference path for ships in ports and waterways based on optimal control. Ocean & Coastal Management 253, 107168. https://doi.org/10.1016/j.ocecoaman.2024.107168

Smierzchalski, R., Michalewicz, Z., 2000. Modeling of ship trajectory in collision situations by an evolutionary algorithm. IEEE Transactions on Evolutionary Computation 4, 227–241. https://doi.org/10.1109/4235.873234

Sun, Y., Bai, D., Han, G., Feng, R., Hao, J., Yao, B., 2025. Resilience maintenance strategy for mixed vehicle traffic on port expressway based on lane management. Ocean & Coastal Management 265, 107645. https://doi.org/10.1016/j.ocecoaman.2025.107645

Sun, Z., Chen, Z., Hu, H., Zheng, J., 2015. Ship interaction in narrow water channels: A two-lane cellular automata approach. Physica A: Statistical Mechanics and its Applications 431, 46–51. https://doi.org/10.1016/j.physa.2015.02.079

Towards a green and just transition, 2023. , Review of maritime transport / United Nations Conference on Trade and Development, Geneva. United Nations, Geneva.

Wang, C., Zhang, X., Gao, H., Bashir, M., Li, H., Yang, Z., 2024. Optimizing anti-collision strategy for MASS: A safe reinforcement learning approach to improve maritime traffic safety. Ocean & Coastal Management 253, 107161. https://doi.org/10.1016/j.ocecoaman.2024.107161

Wang, Y., Liu, R.W., Liu, J., Yang, L., Liu, Y., Piera Eroles, M.A., 2026. Resilient RoRo fleet scheduling for mixed EV and ICEV transport demand: An optimization framework for EV dedicated service strategy. Transportation Research Part E: Logistics and Transportation Review 209, 104719. https://doi.org/10.1016/j.tre.2026.104719

Wang, Y., Meng, Q., Kuang, H., 2018. Jointly optimizing ship sailing speed and bunker purchase in liner shipping with distribution-free stochastic bunker prices. Transportation Research Part C: Emerging Technologies 89, 35–52. https://doi.org/10.1016/j.trc.2018.01.020

Wei, X., Jia, S., Meng, Q., Tan, K.C., 2020. Tugboat scheduling for container ports. Transportation Research Part E: Logistics and Transportation Review 142, 102071. https://doi.org/10.1016/j.tre.2020.102071

Wu, L., Jia, S., Wang, S., 2020. Pilotage planning in seaports. European Journal of Operational Research 287, 90–105. https://doi.org/10.1016/j.ejor.2020.05.009

Xia, Z., Guo, Z., Wang, W., Jiang, Y., 2021. Joint optimization of ship scheduling and speed reduction: A new strategy considering high transport efficiency and low carbon of ships in port. Ocean Engineering 233, 109224. https://doi.org/10.1016/j.oceaneng.2021.109224

Xiao, Y., Li, X., Yin, J., Liang, W., Hu, Y., 2023. Adaptive multi-source data fusion vessel trajectory prediction model for intelligent maritime traffic. Knowledge-Based Systems 277, 110799. https://doi.org/10.1016/j.knosys.2023.110799

Yan, R., Liu, Y., Wang, S., 2024. A data-driven optimization approach to improving maritime transport efficiency. Transportation Research Part B: Methodological 180, 102887. https://doi.org/10.1016/j.trb.2024.102887

Yang, Y., Yan, R., Wang, S., 2024. An efficient ranking-based data-driven model for ship inspection optimization. Transportation Research Part C: Emerging Technologies 165, 104731. https://doi.org/10.1016/j.trc.2024.104731

Yao, Z., Wu, Y., Wang, Y., Zhao, B., Jiang, Y., 2023. Analysis of the impact of maximum platoon size of CAVs on mixed traffic flow: An analytical and simulation method. Transportation Research Part C: Emerging Technologies 147, 103989. https://doi.org/10.1016/j.trc.2022.103989

Zhang, F., Li, J., Zhao, Q., 2005. Single-lane traffic simulation with multi-agent system, in: Proceedings. 2005 IEEE Intelligent Transportation Systems, 2005. Presented at the Proceedings. 2005 IEEE Intelligent Transportation Systems, 2005., pp. 56–60. https://doi.org/10.1109/ITSC.2005.1520219

Zhen, L., Hu, Z., Yan, R., Zhuge, D., Wang, S., 2020. Route and speed optimization for liner ships under emission control policies. Transportation Research Part C: Emerging Technologies 110, 330–345. https://doi.org/10.1016/j.trc.2019.11.004

Zhen, R., Jin, Y., Hu, Q., Shao, Z., Nikitakos, N., 2017. Maritime Anomaly Detection within Coastal Waters Based on Vessel Trajectory Clustering and Naïve Bayes Classifier. J. Navigation 70, 648–670. https://doi.org/10.1017/S0373463316000850