Computers & Industrial Engineering 172 (2022) 108638

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

Modelling an improved ship appointment system for lockage operations of waterway transport

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ARTICLE INFO

Keywords:
Mathematical model
Green transportation
Appointment system
Multi-objective optimization
Lockage scheduling
Three Gorges Dam

ABSTRACT

The traffic congestion problem has become a significant challenge for green shipping of inland waterway transport, resulting in long waiting times and high carbon emissions. Several studies have been conducted to optimize the use of the passing facilities and lockage efficiency, but the improvement of the ship appointment system has not been investigated. In this paper, we formulate new mathematical models for an improved appointment system to manage the ship arrival pattern. With a better matching between the ship arrivals and the lockage capacity, both average waiting time and carbon emissions can be reduced. To achieve this goal, a new nonlinear bi-objective optimization model is formulated to balance the waiting time and the scheduling adjustment. The bisection method with point-wise stationary fluid flow approximation (B-PSFFA) is used to estimate the ship arrivals and calculate the ship waiting time and the associated carbon emissions. The numerical results of a real-world case study at the Three Gorges Dam illustrate that optimizing the appointment quota can effectively adjust the ship arrivals to relieve the waterway transport congestion and reduce carbon emissions. In addition, the number of appointment segments divided within the planning horizon has an impact on the scheduling decisions.

1. Introduction

To achieve the obligation of sustainable development, China, the world's largest emitter of greenhouse gases, has recently announced an ambitious plan to peaking the carbon emissions by 2030 and to reach carbon neutrality by 2060 (Cai et al., 2021; Hu et al., 2021). Achieving these goals of carbon emission reduction is critical to the sustainable socio-economic development of China in the long run. Today, China's carbon emissions account for more than a quarter of the world's total emissions (Wei et al., 2021), whereas the transportation industry is one of the heaviest emitters accounting for the most energy consumption and carbon emissions (Bai et al., 2019). From 2001 to 2018, the cumulative carbon emissions of China's transportation industry have increased by 633.46 million tons, so reducing the carbon emission in the transportation industry is of imperative importance (Liu et al., 2021).

Due to the advantage of low cost and high capacity, waterway transport is an important part of the transportation industry and has grown rapidly over the past decades (Zhang et al., 2021). The waterway freight transport turnover reached 9.73 trillion ton-kilometers in 2016, which constitutes 52.16 % of the aggregate freight transport turnover of China (Zhou et al., 2021). The Yangtze River is one of the busiest "golden waterways" in the world, and the associated carbon emissions from waterway transport have increased drastically in recent years (Tao et al., 2019). Several dams have been constructed on the Yangtze River and its tributaries for water storage and power generation. However, passing these dams requires lockage operations to overcome the water level difference between the two sides, and the long operation time and the capacity limitation of the ship locks have become the major bottleneck for waterway transport on the Yangtze River.

The Three Gorges Dam (TGD) is the most important water conservation project in the Yangtze River. Statistics show that the cargo throughput passing the TGD has reached 146 million tons and 137 million tons in 2019 and 2020, which exceed the designed levels by 46 % and 37 %, respectively. The sharply increasing demands for passing the TGD have resulted in much longer waiting times and more carbon emissions from the ships (Zhao et al., 2020). The waterway traffic congestion problem at the TGD is thus believed to be a major hindrance to green shipping on the Yangtze River (Yan et al., 2017), which has become increasingly focused on due to both economic and environmental concerns (Yuan et al., 2016; Guo et al., 2020). While ships wait

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https://doi.org/10.1016/j.cie.2022.108638
Received 11 January 2022; Received in revised form 9 June 2022; Accepted 4 September 2022

for the passing orders at the anchorage, a large amount of diesel needs to be consumed for electricity generation to maintain the normal life of the crew and the operation of related equipment. This leads to increased carbon emissions and waste generation, which imposes significant impacts and risks on the closed-form ecological environment of the Three Gorges Reservoir (Uusitalo et al., 2019). The annual number of ships waiting at the anchorage reaches approximately 140,000, which results in nearly 4,000 tons of carbon emissions and 3 tons of PM2.5 emissions. Recent data shows that air pollution in the TGD area is becoming increasingly severe (Tan et al., 2019). The waterway traffic congestion is caused by the imbalance between the increasing demands for passing the TGD and the limited lockage capacity during busiest periods (Lalla-Ruiz et al., 2018; Notteboom, 2012; Weng et al., 2020). Thus, the development of an improved ship appointment system for better matching the ship arrivals and the lockage capacity at the TGD is extremely important, which can help to reduce both waiting time and carbon emissions.

At present, the waterway traffic congestion problem at the TGD has been modelled by several researchers (Neagoe et al., 2021). Zhao et al. (2019) and Dong and Lee (2020) studied an efficient ship dispatching problem by optimizing the speed of ships from the waiting area to the gate of the ship lock. Taking into account the carbon emission constraints, a comprehensive model was formulated to optimize the speed of ships, based on which the traffic congestion could be effectively relieved (Norstad et al., 2011; Ge et al., 2021). Considering the capacity utilization of the passing facilities (Yuan et al., 2015), Zhao et al. (2020) and Wang et al. (2013) proposed mathematical models to simultaneously optimize both facility utilization and ship scheduling in passing the TGD. Furthermore, by combining the inland transportation via roads and railways, Yuan et al. (2016) and Ji et al. (2019) investigated the water-inland coordinated transportation problem to relieve the waterway traffic congestion at the TGD. Even though significant research efforts have been spent, the problem of matching the ship arrival and the capacity of the passing facilities through an improved appointment system has not been investigated, and the goal of carbon emission reduction has not been well implemented (Tan et al., 2015). Thus, this paper aims at filling these gaps by providing an improved modeling effort and quantitative analysis.

The remainder of the paper is organized as follows. Section 2 provides a literature review of existing research. Section 3 presents the problem description. Section 4 formulates a queue length estimation model and a bi-objective optimization model for ship appointments. Section 5 introduces the NSGA-II approach for solving the multi-objective optimization problem. Section 6 presents numerical experiments and the discussions of the experimental results. Section 7 concludes the paper with the key findings and suggestions for future research.

2. Literature review

In this section, we reviewed the relevant research works. The congestion problem caused by the demand-capacity mismatch has been investigated in truck scheduling with an appointment system. Phan and Kim (2015) developed a terminal appointment system (TAS) to reduce the truck queues at container terminals, and a genetic algorithm was used to optimize the appointment quota and improve the flexibility of the TAS (Chen et al., 2013b). Mar-Ortiz et al. (2020) proposed an optimization-based decision support system (DSS) for capacity management in container terminals and quota allocation within the planning horizon. In addition, Zhang et al. (2013) formulated a truck appointment optimization model incorporating a secondary queuing network of gates and yards. Torkjazi et al. (2018) developed a new TAS to effectively reduce the operating cost of container terminals.

The consideration of carbon emission reduction and green scheduling in a TAS has become increasingly important (Li et al., 2018; Li et al., 2013). For instance, the impact of carbon emissions was analyzed when a TAS was implemented in the Port of Los Angeles (Namboothiri and Erera, 2008). Zehendner and Feillet (2014) developed a TAS to improve the service level of trucks and minimize the total delay and carbon emissions of the service terminal. Chen et al. (2013a) established a bi-objective model to minimize the waiting time with the minimum changes in the truck arrival pattern. The proposed model considered both the average waiting time and carbon emissions, and a genetic algorithm based on the Pareto front-end heuristic algorithm (PFGA) was developed to solve the optimization problem. Guo et al. (2018) formulated a bi-objective mixed-integer nonlinear programming (MINLP) model to balance the cost-minimization and emission-minimization objectives, and a new evolutionary strategy-based Pareto optimization method (ESMPO) was used to solve the model. Under the limited level of adjustment, Zeng et al. (2015) optimized the truck appointment and scheduling adjustment to effectively reduce the truck queuing time. A bi-level programming model that integrated both truck appointment and crane deployment was developed by Ma et al. (2018), where the total number of adjusted truck arrivals was considered separately.

Even though the use of the TAS has been investigated by many researchers in truck scheduling problems, the development of improved appointment systems for better matching the demand and facility capacity in inland waterway transport has not been investigated. In addition, most research on the TAS focus on the optimization of individual objectives, e.g., the appointment quota of each period, the reduction of average waiting time, etc. For instance, Chen et al. (2013a) considered the average waiting time and carbon emissions, as well as the impact of the total number of truck transfers, but the trade-off among the objectives was not thoroughly investigated to further understand the negative impact. However, the ship appointment system at the TGD is extremely complicated, where two or more objectives are interrelated. For example, the setting of the appointment quota affects the ship arrival adjustment, the waiting time, the associated carbon emissions as well as other environmental impacts. Therefore, these influencing factors need to be holistically taken into consideration in the ship appointment system. In order to fill the literature gaps, we propose a bi-objective MINLP model for optimizing the ship appointment in passing the TGD, which determines the optimal appointment quota and adjusts the pattern of ship arrivals. The bisection method with point-wise stationary fluid flow approximation (B-PSFFA) is used to model the queuing process of ship arrivals at the anchorage, and a nondominated sorting genetic algorithm II (NSGA-II) is used to solve the model.

This paper aims at making the following scientific contributions:

1. A new bi-objective MINLP model is formulated to balance the trade-off between the average waiting time and the schedule adjustment, which helps to relieve the waterway traffic congestion.
2. The model considers the minimization of carbon emissions from the ships waiting at the anchorage. By determining the optimal quota in each period, the ship arrivals and the capacity of passing facilities can be better matched to reduce environmental impacts.
3. Through a real-world case study, the trade-off among various influencing factors in a ship appointment system is revealed, and generic implications can be obtained to help with better decision-making.

3. Problem description

In this section, the ship appointment problem for lockage operations is discussed based on a real-world case at the TGD. At present, two passing facilities, namely the five-stage ship lock and the ship lift, are used to pass the TGD, which are managed by the Three Gorges Navigation Administration (TGNA). Due to the limited service capacity of these two passing facilities, waterway traffic congestions can be caused by a large number of ship arrivals within a short period. In this case, carbon emissions, waste generation, and other environmental impacts will be sharply increased with a large number of ships waiting at the anchorage for a long time, which imposes a high environmental risk to

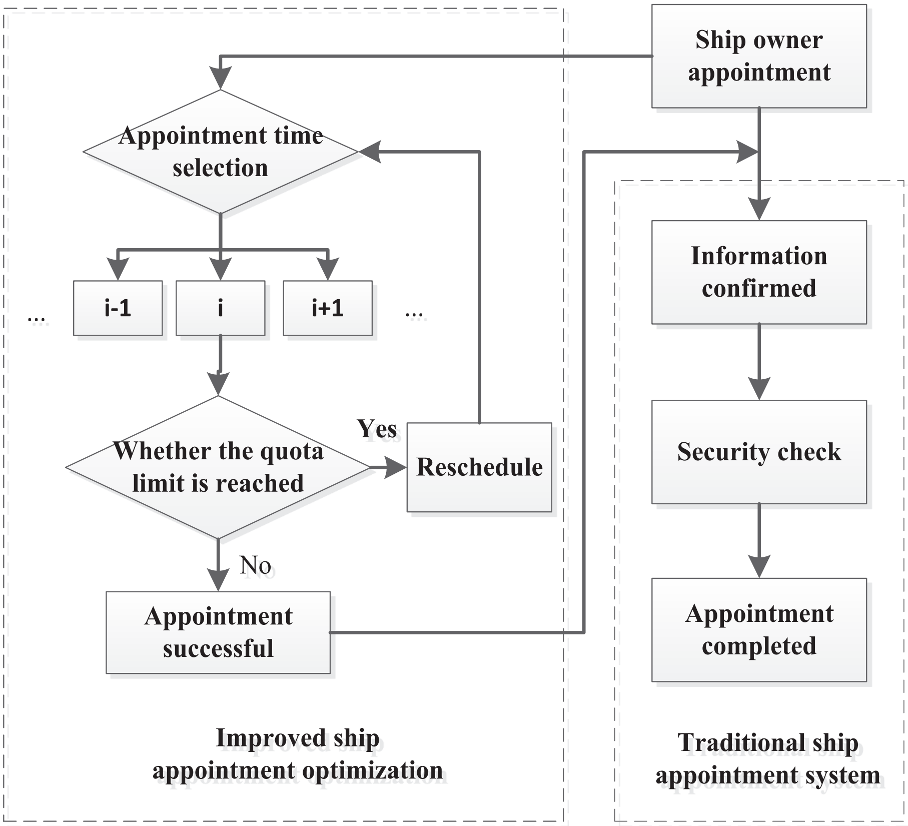

Fig. 1. The improved ship appointment system.

the vulnerable ecosystem in the TGD area. Therefore, it is necessary to reduce the average waiting time and carbon emissions of ships by better managing their arrival patterns, which can help to level the peak and relieve the water traffic congestion.

Today, a passive ship appointment system is used by the TGNA, and the appointment for passing the TGD is completed through a GPS-based remote registration system. The registration consists of four procedures: 1) the appointment request sent by the shipowner; 2) the registration and confirmation of ship-related information; 3) safety inspection; 4) completion of the registration. The Beidou navigation system and GPS are used to collect the real-time positioning information of ships, which is used for safety monitoring and improved scheduling of ships. For example, a ship coming from upstream of the Yangtze River can start the registration when it arrives at the Yunyang Bridge, which is 244.5 km away from the TGD. After completing the registration, ships need to wait for the orders from the TGNA to pass the dam via different facilities.

However, the traditional ship appointment system suffers from several problems. First, this GPS-based remote registration system cannot provide information on the utilization of the passing facilities and the estimated waiting time. The shipowners can only send requests and wait passively for the orders, but they cannot select the preferred time slot. This leads to uncertain waiting times and increased costs for shipowners, while at the same time, generating more environmental impacts in the TGD area. Secondly, due to the uncertainty related to the ship arrivals, the utilization of the passing facilities may significantly vary from time to time, which further complicates the scheduling problem in passing the TGD. Thus, the mismatch problem between the facility capacity and ship arrivals cannot be effectively solved by the traditional ship appointment system.

Thus, in order to better manage the ship arrivals and facility utilization, the framework of an improved ship appointment system is proposed in Fig. 1. Based on the operational schedule and capacity of the passing facilities, a set of appointment periods and the quota of each period are determined by the TAS. This improved ship appointment system is interactive, which allows shipowners to register their preferred time slots to pass the TGD. When the appointment quota of a given period is not reached, the ship will be assigned to its preferred time slot. Otherwise, the ship may be given the nearest adjacent period. In this improved appointment system, shipowners are required to arrive at the anchorage on time or cancel the registration in advance, otherwise, a high penalty will be charged. The improved ship appointment system can effectively solve the demand-capacity mismatch problem, which helps to reduce both the waiting time and carbon emissions at the TGD area.

4. Mathematical model

To formulate the mathematical models of the improved ship appointment system, the following assumptions are made:

1. Ships need to complete the appointment at least 24 h in advance, and the scheduling of ships without an appointment is not considered.
2. Strict penalty measures, e.g., ship credit system, cancellation of appointment, etc., are implemented by the TGNA to ensure the punctuality of ship arrivals, so late arrivals are not considered.
3. The environmental impact is measured by the carbon emissions generated by the ships waiting at the anchorage.
4. The ship lift is mainly used to increase the flexibility of the navigation schedule, so only the appointment of the five-stage ship lock is considered in this paper.

The planning horizon of the ship appointment system is given in set $S = \{1, 2\cdots N\}$, which is indexed by n. The number of daily appointment periods is divided by set $\mathrm{K} = \{1, 2\cdots I\}$, which is indexed by i. In the

Table 1
Definition of parameters and variables.

Input parameters	
N	The planning horizon of the ship appointment system (days)
I	Number of daily appointment periods
A_{ni}	Expected number of ship arrivals of the i^{th} period in day n
W_{ni}	Average waiting time of ships calculated by the B-PSFFA method (h)
λ_{ni}	Number of ships arrived at the i^{th} period in day n
μ_{ni}	Number of ships serviced at the i^{th} period in day n
l_{ni}	Queue length of the i^{th} period in day n
ι	Average service time of a single ship
e_{ni}	Service capacity of the i^{th} period in day n
ω_{ni}	Maximum queuing time of ships at the i^{th} period in day n
l_{max}	Maximum allowable queue length for a given appointment period
M	The total number of ships scheduled within the planning horizon
Derived variables	
λ^j_{ni}	Number of ships arrived at the j^{th} time point in period i
μ^j_{ni}	Number of ships serviced at the j^{th} time point in period i
l^j_{ni}	Length of the ship queue at the j^{th} time point in period i
W^j_{ni}	Average queuing time at the j^{th} time point in period i (h)
ρ^j_{ni}	Utilization of the ship lock at the j^{th} time point in period i
γ_j	Adjustment coefficient of the j^{th} time point
Decision variables	
B_{ni}	Appointment quota given to the i^{th} period in day n
Q_{ni}	Actual ship arrivals at the i^{th} period in day n

queuing model, each appointment period i is further divided into a set of time points $Z = \{1, 2\cdots J\}$ indexed by j. Table 1 presents the parameters, derived variables, and decision variables of the mathematical model.

4.1. *Estimation of the queue length*

The queuing of ship arrivals waiting for passing the dam is a multi-period unsteady queuing process with overflows, in which the pattern of ship arrivals and the service rates of passing facilities change dynamically over time. Therefore, a non-stationary queuing model can be used to model this process and estimate the waiting time of ships (Zeifman et al., 2019). For example, a point-wise stationary approximation (PSA) model was verified under instantaneous traffic intensity conditions, whose results showed that the service rate and the arrival rate had significant impacts on the approximation (Ma and Whitt, 2016). Based on the point-wise stationary approximation (PSA) method, Wang et al. (1996) proposed a point-wise stationary fluid flow approximation (PSFFA) to analyze a non-stationary queuing model with a single server, and the computational results illustrated that the PSFFA was more accurate than the PSA. Chen et al. (2013a) proposed a multi-server non-stationary queuing model that combined the dichotomy with the PSFFA method in order to solve the inverse problem of the complex queuing function. The B-PSFFA method was used for data simulation, and it showed better and more accurate modeling of non-stationary queuing problems.

The queuing of ships is a complex problem, and a non-stationary $M(t)/E_k/c(t)$ queuing model is thus developed in this paper to analyze the performance of the improved ship appointment system. The B-PSFFA method is used to effectively solve the overloading problem of ships in passing the TGD (Chen et al., 2013a). Besides, it is also capable to model the pattern of ship arrivals at the anchorage. Based on the service rate of the five-stage ship lock, Eq. (1) determines the number of time points in each appointment period. The rate of ship arrivals and the service rate are calculated at each time point using Eqs. (2) and (3), respectively. Eq. (4) calculates the queue length of ships based on the principle of flow balance, with which Eq. (5) estimates the ship's waiting time. Eq. (6) shows the approximation developed by Cosmetatos George (1976) for calculating the corresponding queue length. In Eqs. (7) and (8), instead of inverting the complex formula, we propose to calculate the estimated ρ^{j*}_{ni} by combining the Cosmetatos' approximation and a bisection method. The basic idea of the bisection method is to repeatedly bisect an interval and select the sub-interval, in which ρ^{j*}_{ni} must be within it. To improve the level of confidence of ρ^{j*}_{ni} calculated, a bisection needs to be iterated a number of times. The above queue length calculation process is illustrated in Fig. 2, and a brief description of the bisection method is shown in Fig. 3.

$$J_{ni} = \mu_{ni}, \forall n \in S, i \in K \tag{1}$$

$$\lambda^j_{ni} = \frac{\lambda_{ni}}{J_{ni}}, \forall n \in S, i \in K, j \in Z \tag{2}$$

$$\mu^j_{ni} = \frac{\mu_{ni}}{J_{ni}}, \forall n \in S, i \in K, j \in Z \tag{3}$$

$$l^j_{ni} = l^{j-1}_{ni} + \lambda^j_{ni} - \mu^j_{ni}\rho^j_{ni}, \forall n \in S, i \in K, j \in Z \tag{4}$$

$$W^j_{ni} = \frac{l^j_{ni}}{\mu^j_{ni}\rho^j_{ni}}, \forall n \in S, i \in K, j \in Z \tag{5}$$

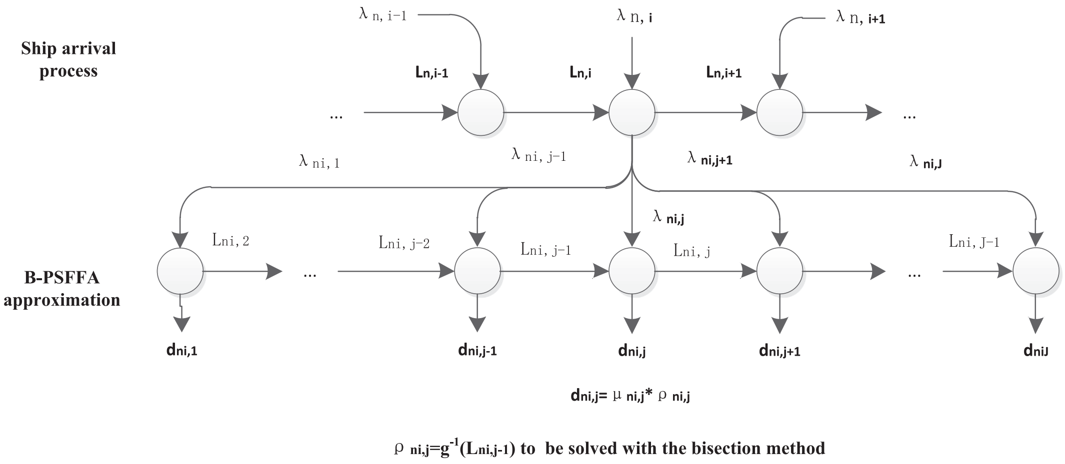

Fig. 2. The B-PSFFA approximation method.

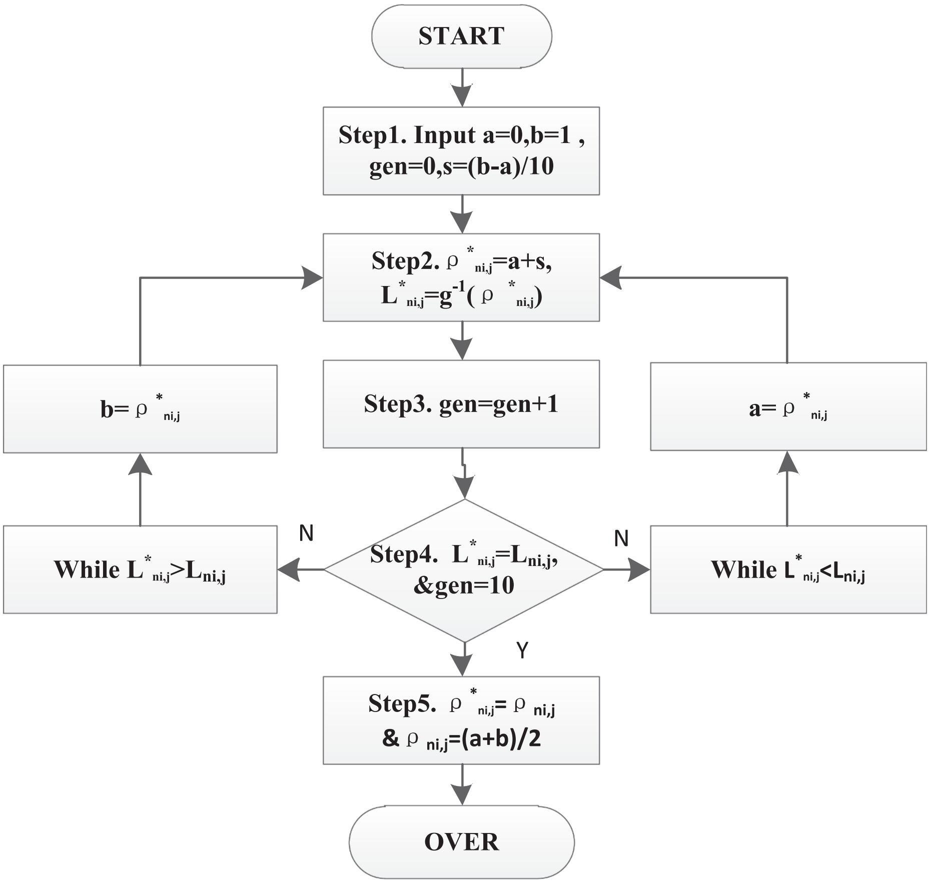

Fig.3. The bisection method in the B-PSFFA approach.

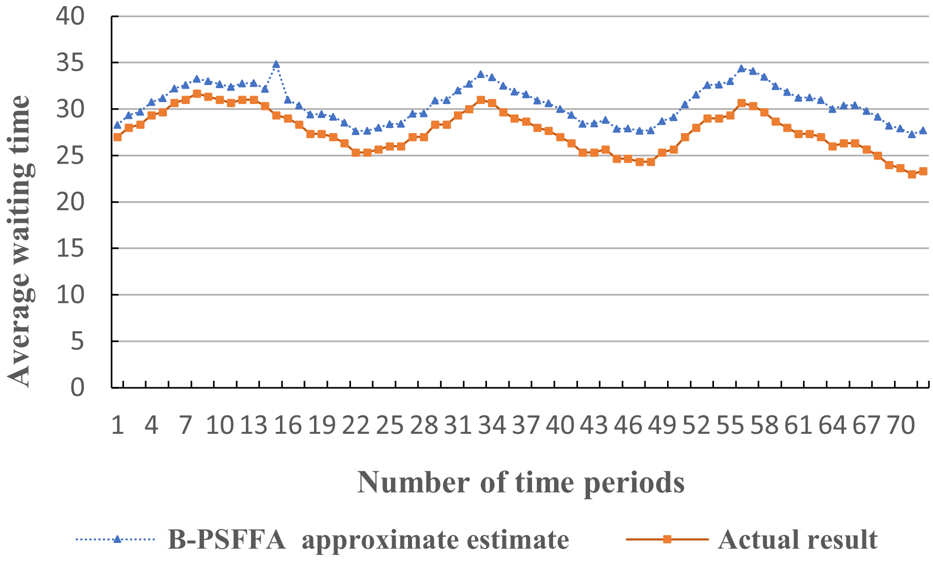

Fig. 4. Comparison between the approximation results and the actual arrivals ($i = 24$).

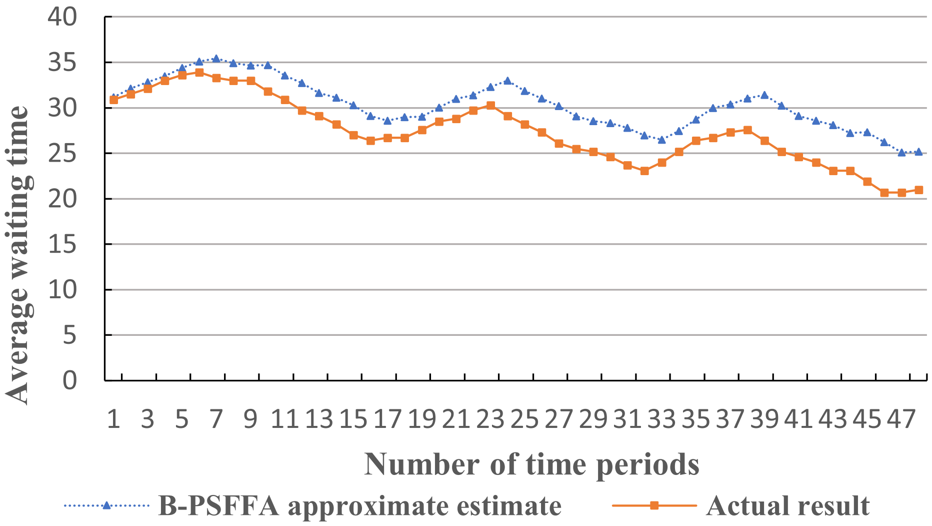

Fig. 5. Comparison between the approximation results and the actual arrivals ($i = 16$).

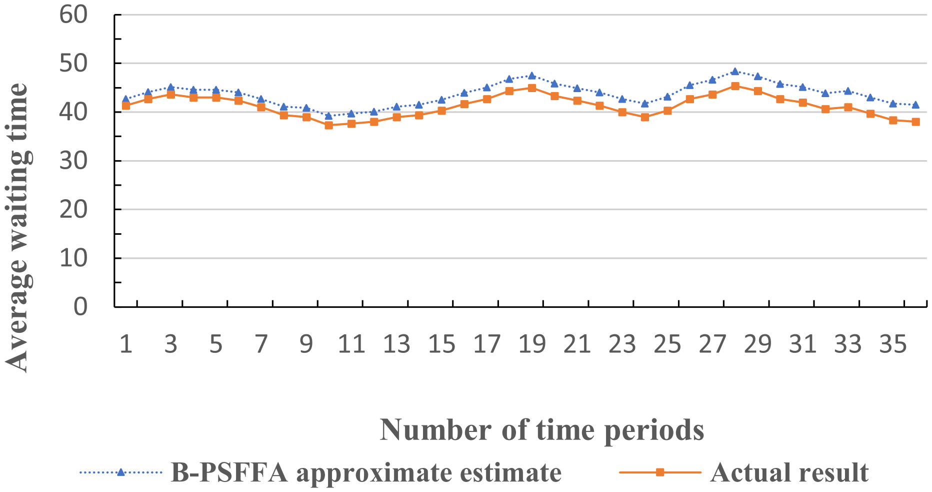

Fig. 6. Comparison between the approximation results and the actual arrivals ($i = 12$).

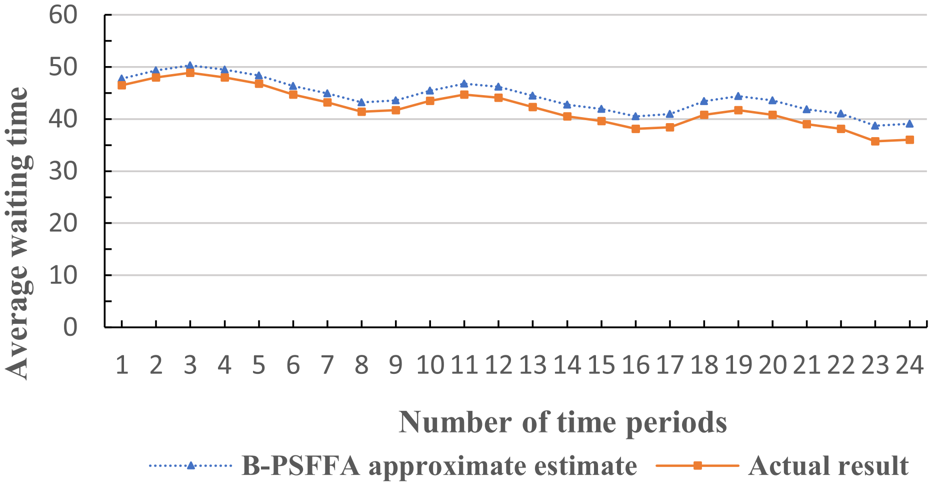

Fig. 7. Comparison between the approximation results and the actual arrivals ($i = 8$).

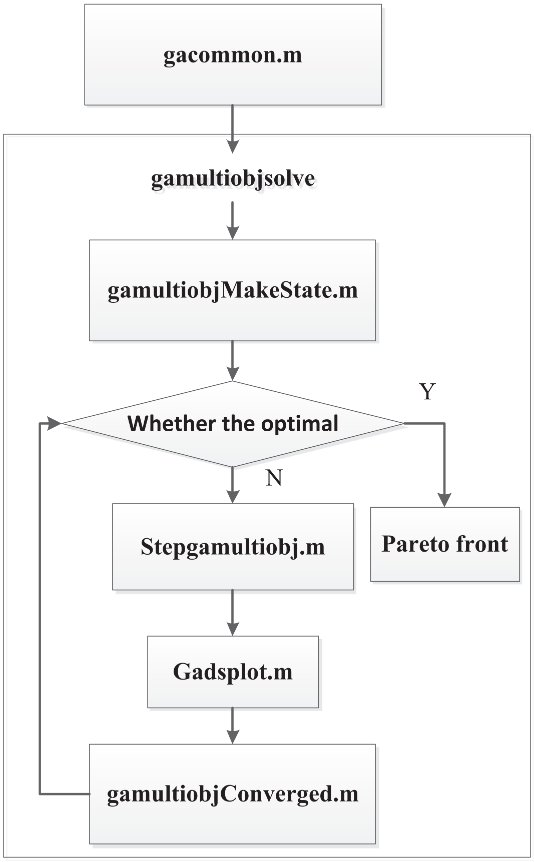

Fig. 8. The gamultiobj function.

$$l = g(\rho, c) = \frac{(\rho c)^{c+1}}{c!(1-\rho)^2}\left\{\sum\nolimits_{n=0}^{c-1}\frac{(\rho c)^n}{n!} + \frac{(\rho c)^c}{c!(1-\rho)}\right\}^{-1}\left\{\frac{1+\frac{1}{k}}{2} + \frac{(1-\frac{1}{k})(1-\rho)(c-1)\sqrt{4+5c}-2}{32\rho c}\right\} \tag{6}$$

$$\rho_{ni}^{j*} = g^{-1}\left(l_{ni}^{j-1}\right), \forall n \in S, i \in K, j \in Z \tag{7}$$

$$\rho_{ni}^{j} = \rho_{ni}^{j*} \times \gamma_j = \rho_{ni}^{j*} \times \left(1 - 1.09 \times \left(c_{ni}^{0.866} \times \left(\sum_i \mu_{ni}^{j}\right)^{1.045}\right)^{-1}\right), \forall j \in Z \tag{8}$$

In this paper, several numerical experiments are performed with real-world data to test the effectiveness of the B-PSFFA method in modeling the characteristics of the ship queuing at the TGD. The experimental results are compared with the real data at four anchorages, i.e., Shawan, Xianrenqiao, Baisuixi, and Quxi, and three dangerous goods anchorages, i.e., Miaohe, Lanling River, and Shanmuxi, from May 24 to 26, 2021. Four scenarios with different divisions of daily appointment periods, i.e., 1 h (i = 24), 1.5 h (i = 16), 2 h (i = 12), and 3 h (i = 8) were taken into account in the experiments, and the parameters were set to $c = 7, k = 4$. Based on the pattern of ship arrivals, the B-PSFFA method calculates the queue length and the average waiting time.

Figs. 4-7 illustrate the comparisons between the approximation results and the real data in the four scenarios. The root mean square error (RMSE) is used to reflect the degree and effect of the deviation between the approximation value and the real data (Zeng et al., 2015). The RMSEs between the approximation results of the B-PSFFA and the real data in the four scenarios are 3.06, 3.24, 2.51, and 2.24, respectively. The relatively small RESMs in all test scenarios indicate that the B-PSFFA approximation method can effectively estimate the queue length of ships at the TGD. Besides, fewer appointment periods may lead to an improved approximation result.

4.2. *Optimization model*

A bi-objective MINLP is formulated to optimize the ship appointments in passing the dam. Eq. (9) is the first objective function that minimizes the average waiting time of ships. Eq. (10) minimizes the ship adjustment rate within a given period due to the insufficient capacity of the five-stage ship lock. It is noteworthy that this objective function will become 0 when the expected ship arrival is less than the facility capacity.

$$MinZ_1 = \frac{\sum_{n=1}^{N}\sum_{i=1}^{I} W_{ni}Q_{ni}}{\sum_{n=1}^{N}\sum_{i=1}^{I} Q_{ni}} \tag{9}$$

$$MinZ_2 = \frac{\sum_{n=1}^{N}\sum_{i=1}^{I} max\{A_{ni} - B_{ni}, 0\}}{\sum_{n=1}^{N}\sum_{i=1}^{I} A_{ni}} \tag{10}$$

$$s.t. \sum_{n=1}^{N}\sum_{i=1}^{I} Q_{ni} = \sum_{n=1}^{N}\sum_{i=1}^{I} A_{ni} \tag{11}$$

$$0 < Q_{ni} \le B_{ni}, \forall n \in S, i \in K \tag{12}$$

$$[Q_{11}, Q_{12}, \cdots, Q_{NI}] = f_{\text{adjust}}(A_{11}, A_{12}, \cdots, A_{NI}, B_{11}, B_{12}, \cdots, B_{NI}) \tag{13}$$

$$l_{n,i+1} = max\{l_{ni} + \lambda_{ni} - d_{ni}, 0\}, \forall n \in S, i \in K \tag{14}$$

$$0 \le l_{ni} \le l_{max} \tag{15}$$

$$Q_{ni} = \lambda_{ni} = \sum_{j=1}^{J} \lambda_{ni}^{j}, \forall n \in S, i \in K \tag{16}$$

$$d_{ni} = \mu_{ni}\rho_{ni}, \forall n \in S, i \in K \tag{17}$$

$$\mu_{ni} = \frac{24}{I\iota}, \forall n \in S, i \in K \tag{18}$$

$$0 \le \rho_{ni} \le 1, \forall n \in S, i \in K \tag{19}$$

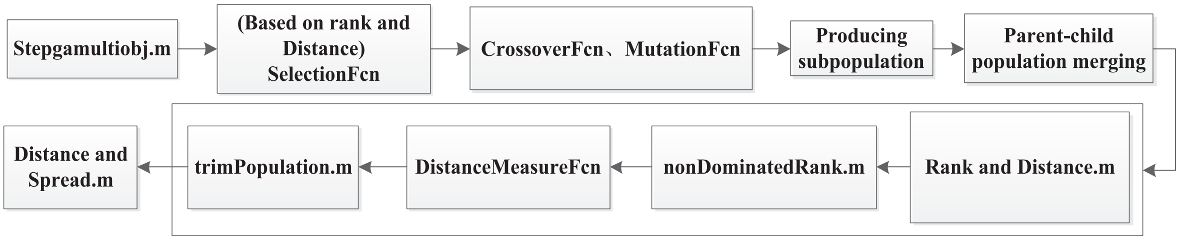

Fig. 9. The Stepgamultiobj function.

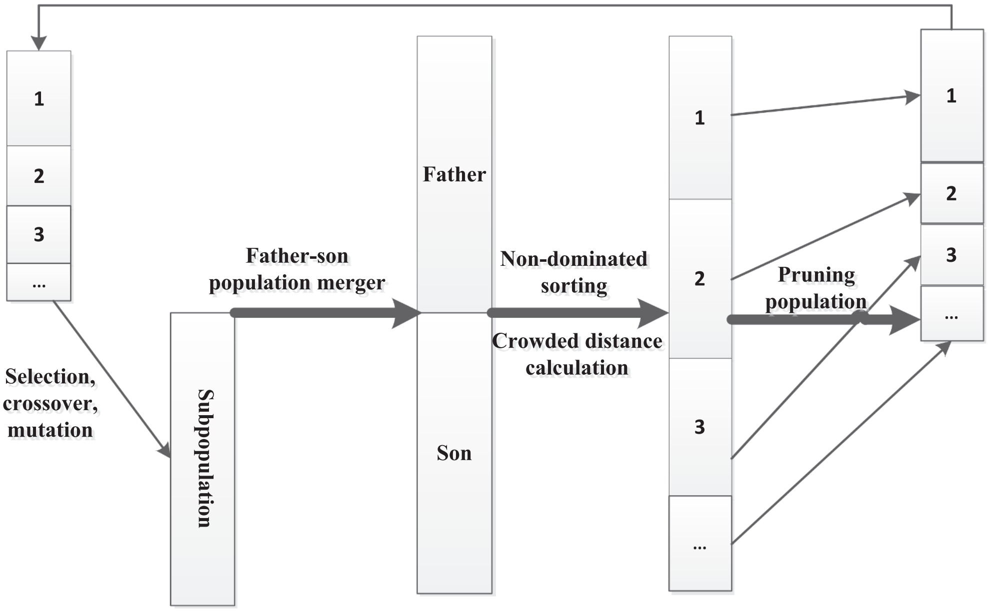

Fig. 10. The NSGA-II procedures of the gamultiobj function.

$$W_{ni} = \frac{l_{ni}}{d_{ni}}, \forall n \in S, i \in K \tag{20}$$

$$0 \le W_{ni} \le \omega_{ni}, \forall n \in S, i \in K \tag{21}$$

$$0 \le B_{ni} \le e_{ni}, \forall n \in S, i \in K \tag{22}$$

$$B_{ni} \in Z^{+}, \forall n \in S, i \in K \tag{23}$$

The model is restricted by constraints (11–23). Constraint (11) ensures that all the ships within the overall appointment period can be scheduled for passing the TGD. Constraint (12) guarantees the number of ships served in each appointment period cannot exceed the allocated quota. Eq. (13) establishes a ship adjustment function to balance the gap between the expected ship arrivals and the allocated quota in each appointment period. When $A_{ni} > B_{ni}, Q_{ni} = B_{ni}$, and it means this appointment period is fully booked, and in this case, the exceeded amount of ship appointments will be adjusted to the nearest adjacent periods where $A_{ni} \le B_{ni}$. Thus, in these periods, Q_{ni} equals to A_{ni} plus the adjusted appointments from other periods. Eq. (14) calculates the change of the queue length in each appointment period. Constraint (15) sets an upper bound of the queue length. Constraints (16–18) calculate the arrival rate of ships, the departure rate, and the service rate of each appointment period. Constraint (19) is the capacity constraint that requires the estimated facility utilization cannot exceed 1. Constraint (20) calculates the average waiting time within each appointment period, and an upper bound is given in constraint (21). Constraint (22) sets the upper bound of the allocated quota in each appointment period, which is restricted by the capacity of the five-stage ship lock. The domains of the decision variables are specified in constraint (23).

4.3. *Carbon emission estimation*

The carbon emissions related to waterway transport is an extensively focused issue (Guo et al., 2018; Howitt et al., 2010). One of the most popular ways to estimate the carbon emissions of ships is based on fuel consumption, and the ratio between fuel consumption and carbon emissions is called the carbon emission factor (CEF). Bialystocki and Konovessis (2016) and Kontovas (2014) suggest the CEF of ships is 3.082, which means consuming 1 ton of fuels will generate 3.082 tons equivalent carbon emissions. Many factors affect fuel consumption, and the most important ones are related to the ship's speed and payload. Zhen et al. (2016) suggest that the fuel consumption during sailing is proportional to the average sailing speed powered by 3, which can be calculated by $f(v) = k_1 v^3$. In fact, more fuels are consumed when a ship sails at a low speed. For example, the ships waiting at an anchorage may yield more fuel consumption.

$$f(v, \omega) = k_1 (p + v^q)(\omega + a)^{2/3} \tag{24}$$

$$f_m = k_1 p (\omega_m + a_m)^{2/3}, \forall m \in M \tag{25}$$

$$CE_m = \alpha_{CO_2} f_m, \forall m \in M \tag{26}$$

In this paper, the method provided by Kontovas (2014) is employed to obtain a more accurate estimation of the fuel consumption and carbon emissions of ships. Eq. (24) calculates the fuel consumption, where v is the average speed of the ship,ω is the shipload (tons), and a is the ship's weight (tons). Parameters k_1, p, q are adjustment parameters, where $k_1 > 0$, $p \ge 0$, $q \ge 3$. Parameter k_1 adjusts ship-related characteristics and loading conditions, and p adjusts fuel consumption at a low speed. Eq. (25) calculates the fuel consumptions of the ships waiting at the anchorages, and the associated carbon emissions are estimated by Eq. (26).

5. Solution method

The improved ship appointment optimization problem for passing the TGD is a multi-objective MINLP, which is NP-hard and requires significant computational efforts. Heuristic and metaheuristic algorithms have been well proved to yield high-quality approximations to solve such problems within a reasonable time (Shang et al., 2021; Alizadeh et al., 2020). In this regard, the non-dominated sorting genetic algorithm II (NSGA-II) developed by Márquez et al. (2008) and Sardou and Ameli (2016) has been widely used to calculate the Pareto optimal solutions of various large-scale multi-objective optimization problems. In this paper, the gamultiobj function of MATLAB is used to code and solve this bi-objective optimization problem, and Fig. 8 illustrates the structure of the gamultiobj function based on genetic algorithm.

In the iterative process of the gamultiobj function, the Stepgamultiobj function is of key importance, whose structure is shown in Fig. 9. The procedures of the NSGA-II implemented in this paper are given as follows:

Step 1: Population initialization is the first step. A set of initial

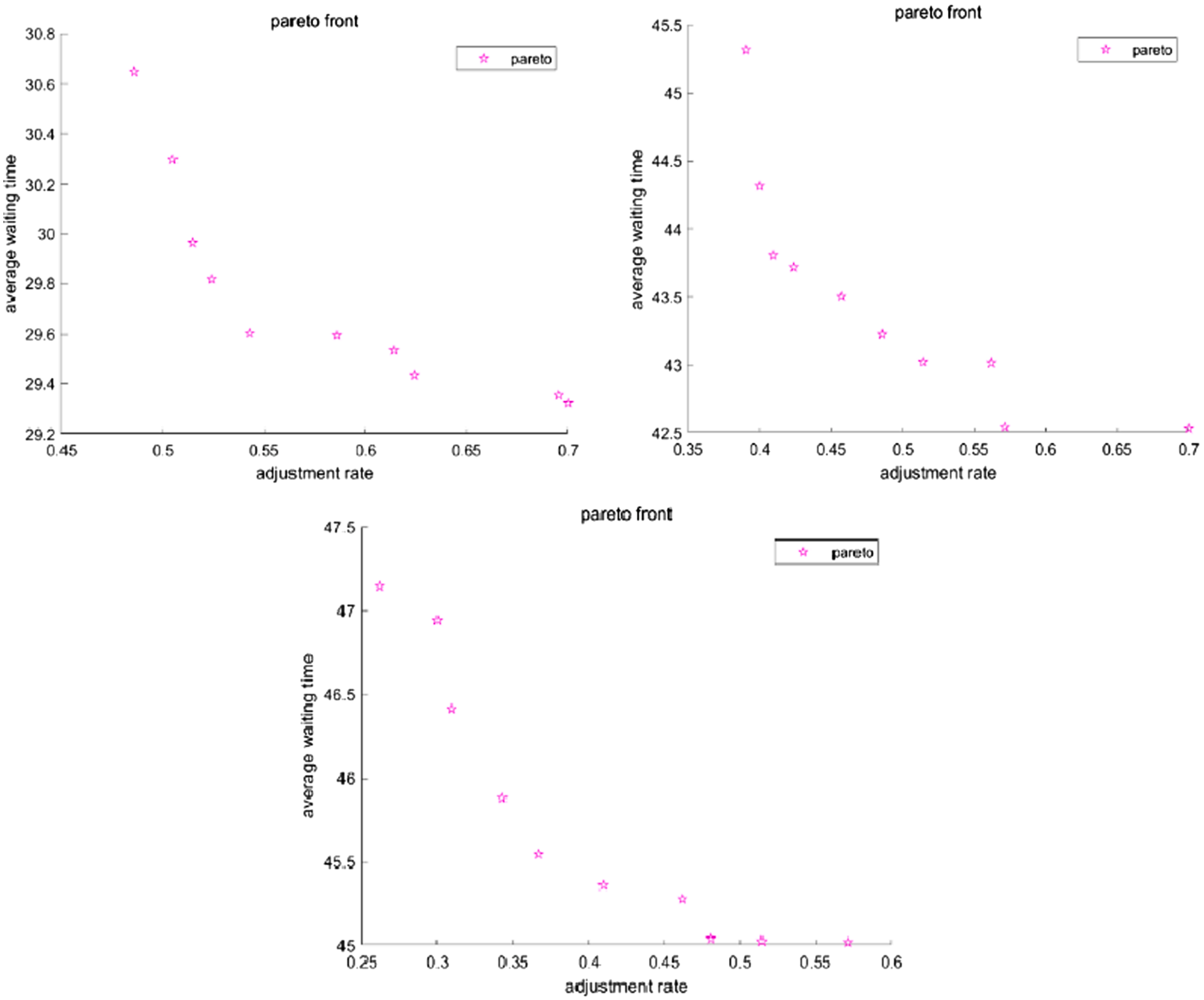

Fig. 11. Pareto optimal solutions in the test scenarios.

Table 2
Selected Pareto optimal solutions in each scenario.

Pareto solution	Scenario 1		Scenario 2		Scenario 3	
	Objective Z1	Objective Z2	Objective Z1	Objective Z2	Objective Z1	Objective Z2
1 (min Z1)	29.32	0.70	42.53	0.69	45.02	0.57
2	29.35	0.69	42.54	0.57	45.03	0.51
3	29.43	0.62	43.01	0.56	45.04	0.48
4	29.53	0.61	43.02	0.51	45.27	0.46
5	29.60	0.59	43.22	0.49	45.36	0.41
6	29.61	0.54	43.50	0.46	45.55	0.37
7	29.81	0.52	43.72	0.42	45.88	0.34
8	29.96	0.51	43.81	0.41	46.41	0.31
9	30.30	0.50	44.32	0.40	46.94	0.30
10 (min Z2)	30.65	0.49	45.32	0.39	47.15	0.26

solution $\{B_{11}, B_{12}, \cdots, B_{NI}\}$ (population) is first generated randomly, and the number of elements in each solution (genes) is determined by the number of appointment periods within the planning horizon. The genes represent the appointment quota in each appointment period, which is restricted by the capacity of the passing facility (μmax_{min}. The population size was set to 100 in the numerical experiments.

Step 2: Next, the Fitness of the individual solutions is calculated and evaluated. The B-PSFFA method is used to model the queuing characteristics of ship arrivals at the anchorage, and the average waiting time is then calculated to update the respective elements in the objective functions. A weighted sum (Eq. (27)) is used to evaluate the fitness of individual solutions, where $\omega_1 + \omega_2 = 1$. The fitness of the individual solution is stored, and a smaller fitness leads to a better trade-off between the two objective functions. The deviation of the fitness function (TolFun) was set to 1e-100.

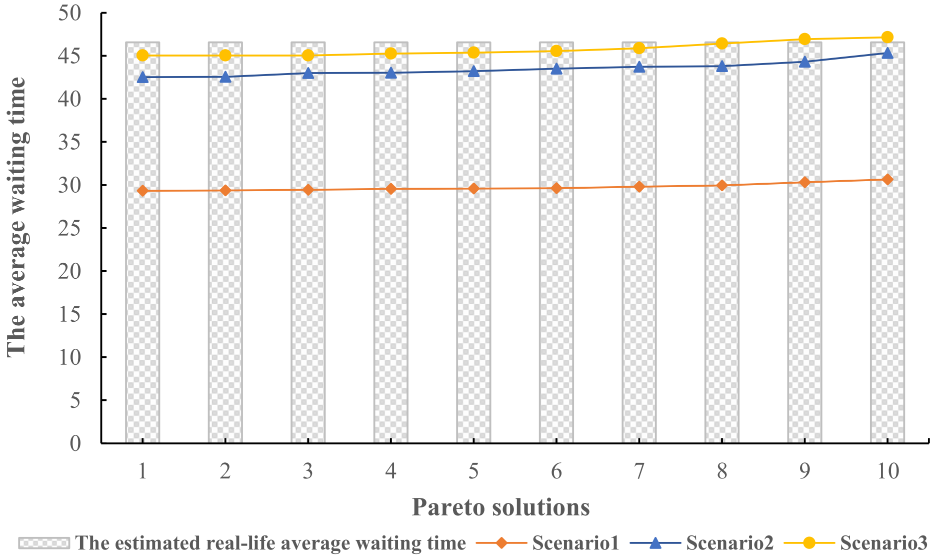

Fig. 12. Comparision of the average ship waiting time under real-life conditions (Estimated real-life ship waiting time vs the three improved scenarios).

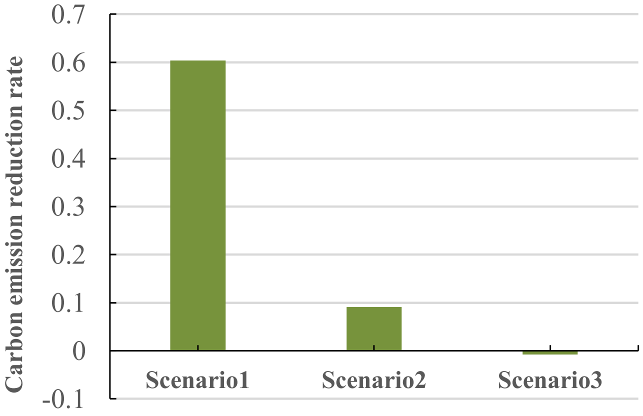

Fig. 13. Carbon emission reduction rate in the three scenarios.

$$Fitness = \omega_1 {}^* Z_1 / Z_{1_{Min}} + \omega_2 {}^* Z_2 / Z_{2_{Min}} \tag{27}$$

Step 3: The best individual solutions are selected. In this paper, the selectiontournament.m function is employed. The selection is based on rank and distance, where the individual solution with a smaller rank is selected regardless of the crowding distance. When two or more solutions have the same rank, the one with a larger crowding distance is selected, because a larger crowding distance has a better population diversity. Then, the fitness value of each individual solution is compared, and the ones with the best fitness value are selected to yield the next generation population. The maximum fraction of the individual solutions selected can be restricted by the ParetoFraction coefficient. The value was set to 0.1.

Step 4: Crossover, mutation, child population, and father-son population merger are performed in this step. Crossover refers to the selection of two individuals from the parent, and a new individual is generated through the crossover operation. Mutation is to select an individual in the parent to generate a new individual in the offspring. Fig. 10 illustrates the operations in this step. The probabilities of crossover and mutation were set to 0.9 and 0.1 in the experiments.

Step 5: Termination criteria are determined. The termination of the NSGA-II is based on the function called Distance and Spread. This function calculates the average distance and spread of the population, where spread is an important measure to evaluate the termination criteria with the gamultiobjConverged function. The search terminates if the Pareto optimal solution cannot be improved after a few interactions (200 in this experiment). Otherwise, it will return to step 2.

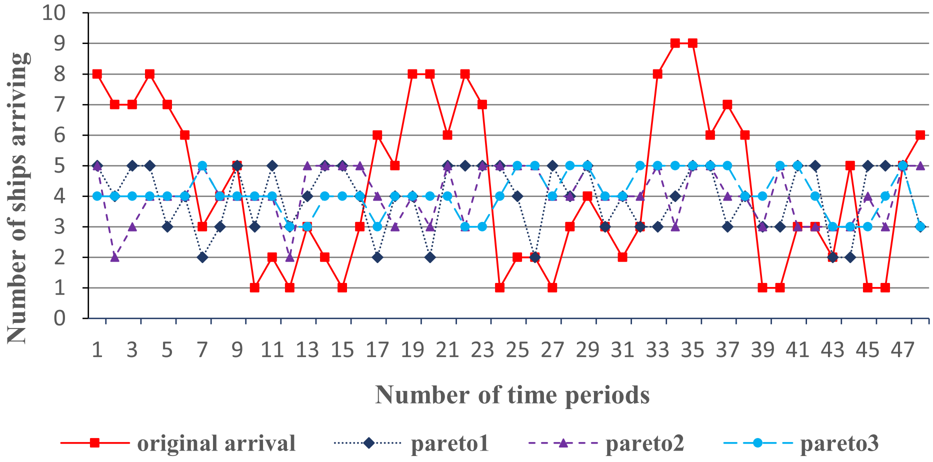

Fig. 14. Ship arrival patterns in scenario 1 ($i = 16$).

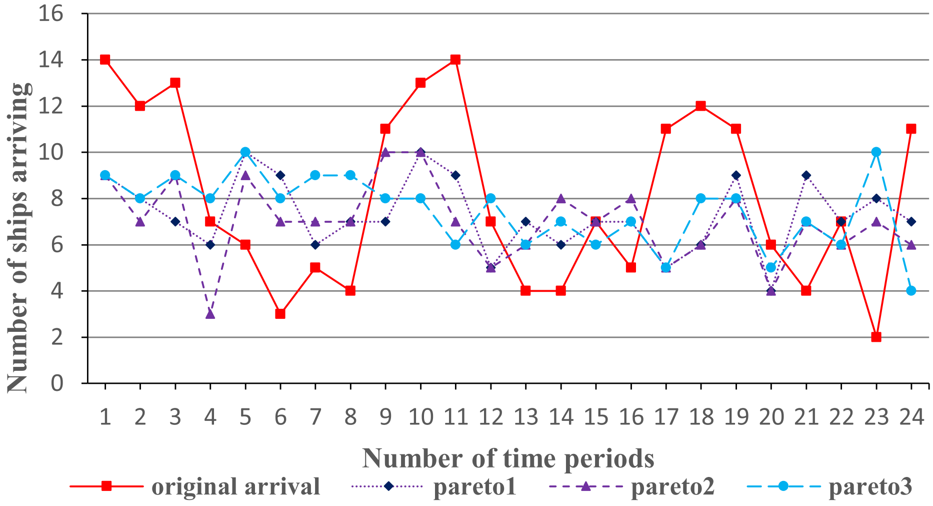

Fig. 15. Ship arrival patterns in scenario 2 ($i = 8$).

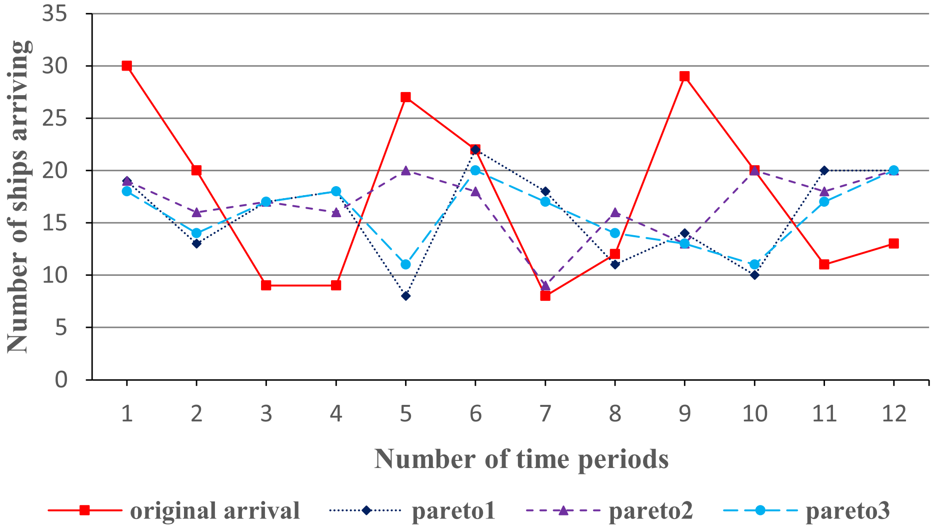

Fig. 16. Ship arrival patterns in scenario 3 ($i = 4$).

6. Case study

In order to show the effectiveness and applicability of the improved ship appointment system, a set of numerical experiments based on the real-world data at the TGD is performed in this section. The planning horizon was set between May 24th and May 26th, 2021, and the real data of ship arrivals and the number of ships scheduled to pass the TGD was collected and implemented in the experiments. Within the planning horizon, we considered three scenarios with $i = 16$, $i = 8$, $i = 4$. The lengths of each appointment period in the three scenarios were set to 1.5 h, 3 h, and 6 h, respectively. The division of the daily appointment periods is based on the fact that a new lockage at the TGD starts approximately every 1.5 h. The computation was performed by MATLAB 2019b on a computer with Intel Core 4 3.2 Hz CPU and 4 GB RAM. The ParetoFraction was set to 0.1, which led to 10 Pareto optimal solutions. The population size was set to 100.

Fig. 11 shows the Pareto optimal solutions obtained in each scenario. Table 2 presents the values of the two objective functions of the Pareto optimal solutions with 50 repetitions. The computational results reveal the trade-off between the average waiting time and the ship adjustment rate, which indicates more adjustments are needed during the busiest season of waterway transport to reduce the average waiting time and carbon emissions in passing the TGD. For instance, in scenario 1, the average waiting time can be reduced to 29.32 h with a ship adjustment rate of nearly 0.7. In contrast, with a minimum ship adjustment rate at 0.49, the average waiting time increases to 30.65 h. Based on the historical data, the average waiting time is approximately 60 h in this period (Yuan et al., 2016; Zhao et al., 2020). Thus, using this improved ship appointment system may significantly reduce the average waiting time by adjusting the ship arrivals.

It is noteworthy that, in scenario 2, the 10th Pareto optimal point obtained can be considered a near dominated solution to point 9. Besides, in scenario 3, the 9th and 10th Pareto optimal solutions can be considered near-dominated solutions. The computational results also show that the division of the daily appointment periods has significant impacts on both objective functions. Within the three-day planning horizon, the total appointment periods in the three scenarios are 48, 24, and 12, respectively. The performances of the two objectives are by no means identical in these three scenarios. When Z1 is optimized, the average waiting time in scenario 1 can be reduced by 31.06 % and 34.87 % compared with that in scenarios 2 and 3. However, in this case, the ship adjustment rates in scenarios 2 and 3 are 18.57 % and 31.43 % less than that in scenario 1.

For the comparison purpose, we randomly generated the waiting

Table A1
The waiting time generated for 240 ships passing the TGD between May 24th and May 26th, 2021.

Ship groups	The estimated waiting time of each ship in each group (hours)					
	1	2	3	4	5	6
1	46	44	44	45	46	44
2	47	45	48	44	43	47
3	46	49	43	47	46	46
4	47	45	45	46	45	44
5	48	50	45	47	46	46
6	49	44	46	43	48	48
7	49	47	45	42	47	47
8	50	44	45	44	47	48
9	46	49	50	46	45	50
10	48	50	45	42	48	47
11	46	45	48	49	47	46
12	50	45	45	44	45	45
13	46	44	45	45	48	47
14	48	45	44	46	43	45
15	45	47	47	44	44	47
16	45	46	44	50	45	47
17	48	45	45	42	42	44
18	45	48	47	45	44	44
19	46	45	44	45	45	49
20	44	46	42	44	46	48
21	45	45	47	43	44	47
22	43	47	43	45	45	45
23	45	45	45	48	47	48
24	49	50	48	50	46	45
25	46	49	47	50	47	48
26	49	49	46	50	46	49
27	47	47	46	49	45	45
28	48	47	50	49	50	49
29	48	49	49	49	46	46
30	49	47	47	46	46	47
31	45	47	45	46	47	44
32	48	48	47	46	47	49
33	49	45	50	47	50	50
34	45	46	46	48	48	48
35	46	48	48	46	49	46
36	45	45	50	46	48	45
37	48	48	48	49	49	49
38	48	48	49	49	47	48
39	48	45	46	47	49	50
40	48	50	50	48	46	46

time of 240 ships from the parameter interval based on the observation at the TGD from May 24th and May 26th, 2021, as shown in Appendix A (Table A1). These values were used to estimate real-world situations, which resulted in an average ship waiting time of approximately 46.56 h. Fig. 12 compares the average waiting time of the real-world situation at the TGD (without ship arrival adjustment) with the three improved scenarios by employing the proposed ship appointment system. The results illustrate that the proposed ship appointment system has a good potential to yield high-quality decisions that can help effectively reduce the average ship waiting time in close-to real-life conditions.

In general, when the planning horizon is divided into more appointment periods with a shorter length, the average waiting time and the carbon emissions can be effectively reduced. However, the ship adjustment rate increases significantly due to the reduced flexibility within a shorter planning period. The carbon emissions in the three test scenarios were calculated and compared with that of the traditional ship appointment system, and only the ships that passed the TGD via the five-stage ship lock were included in the calculation. Fig. 13 shows the percentage of the carbon reduction in each scenario when Z1 is optimized. In scenarios 1 and 2, the carbon emissions can be reduced by 60.4 % and 9.2 %, respectively. However, the carbon emissions increase by 0.3 % in scenario 3. The results suggest that the improved ship appointment system can, in general, reduce the carbon emissions from ships passing the TGD. However, the environmental impacts may be increased if the appointment periods are improperly divided over the planning horizon. Therefore, it is important to set the appropriate appointment periods in the improved system in order to achieve reduced waiting time and carbon emissions while maintaining the ship adjustment rate within an acceptable level.

Finally, we investigated the effectiveness of the improved ship appointment system in adjusting the ship arrival patterns at the TGD in order to better match the capacity of passing facilities. Figs. 14, 15, and 16 show the results of ship arrival patterns of three selected Pareto optimal solutions in each test scenario, which are compared with the original ship arrival patterns at the TGD within the planning horizon. The comparison results reveal that the original ship arrivals are unevenly distributed over different periods. During the peak periods, the ships that arrived largely exceeded the service capacity of the passing facilities, which results in a long waiting time and large carbon emissions. By implementing the improved ship appointment system, the ship arrival patterns can be flattened with more even quota allocation in different appointment periods to better match the service capacity of the passing facilities at the TGD.

It is noteworthy that, with a shorter length of an appointment period, a flatter ship arrival pattern is observed in scenario 1. This result indicates implementing a shorter length of appointment period may lead to more evenly distributed ship arrivals within the planning horizon, which helps to better match the service capacity and reduce the waiting time and carbon emissions. However, this results in a higher adjustment rate of ships due to the lack of flexibility. In scenarios 2 and 3, the ship arrivals are adjusted at lower levels, so the ship adjustment rate can be improved compared with that in scenario 1. However, longer waiting times and more carbon emissions are yielded in these two scenarios. Thus, the computational results show that the improved ship appointment system can effectively relieve the waterway traffic congestion at the TGD during peak periods by adjusting the ship arrival pattern. In addition, the length of the daily appointment periods may yield significant impacts on the average waiting time, ship adjustment rate, and carbon emissions.

7. Conclusion

To solve the waterway transport congestion problem, this research proposes new mathematical models for an improved ship appointment system for reducing the average waiting time and carbon emissions through better matching the ship arrival pattern and the service capacity of the passing facilities. A B-PSFFA is first formulated to approximate the ship arrivals, and a new bi-objective MINLP model is then established to balance the trade-off between the average waiting time and the adjustment rate. An NSGA-II is used to solve the bi-objective optimization problem, and a real-world case study at the TGD is performed to show the applicability of the proposed model and algorithm. The experimental results show that, with the proper setting of the appointment periods and quota, the average waiting time and carbon emissions can be effectively reduced while, at the same time, the ship adjustment rate can be maintained at an acceptable level. However, the length of the appointment period has a significant impact on the performance of both objectives.

Based on the modeling and numerical experiments, three generic implications can be obtained to better plan the lockage operations in waterway transport:

1. The improved ship appointment system may help to reduce the average waiting time and carbon emissions by adjusting the ship arrival pattern. In this regard, the proposed mathematical model can be used to determine the optimal appointment quota in each period.
2. Through the optimization of the appointment quota in each period, the service capacity of the passing facilities may be better matched with the re-scheduling of ship arrivals from peak periods to off-peak periods, and this can relieve the waterway transport congestion for passing a dam.

3. The division and length of the appointment periods within the planning horizon may yield significant influences. In general, a shorter appointment period may require more ship adjustments to achieve more even quota distributions, and this results in a more effective reduction in the average waiting time and carbon emissions. On the other hand, a longer appointment period may be less effective in adjusting the ship arrivals and reducing carbon emissions

For further improvements, three suggestions are made to tackle the limitations of the current research. First, the uncertainties related to ship arrivals should be considered. Although strict penalties are implemented, the delay of ship arrivals is still inevitable. Besides, the time for safety inspection before entering the anchorage may vary significantly in different conditions, which poses uncertainties of on-time ship arrival. Thus, the uncertainty issues need to be properly treated in the optimization models. Second, under the space limitation of the lock chamber, the different sizes of the ships may yield significant impacts on the service capacity of the lockage operations and on the appointment quota in each period (Zhao et al., 2020), so future research is expected to holistically model and investigate this impact. Third, more real-life data is needed to validate the proposed ship appointment system to obtain reliable implications.

CRediT authorship contribution statement

Xu Zhao: Conceptualization, Methodology, Investigation, Supervision. **Shun Liu:** Conceptualization, Methodology, Software, Data curation, Investigation, Writing – original draft. **Pan Gao:** Conceptualization, Methodology, Investigation, Supervision. **Hao Yu:** Methodology, Investigation, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This research is supported by the Philosophy and Social Science Research Project of the Hubei Education Department (No. 19Q033).

Appendix A

See Table A1.

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