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A two-stage decision-support system for floating debris collection in reservoir areas

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ABSTRACT

The accumulation of floating debris is one of the main challenges of water conservancy projects, which may pollute the vulnerable ecosystem of the reservoir area and impose significant risks on waterway transportation and dam operations. Due to the dynamicity and uncertainty caused by water flow, the collection of floating debris is much more complicated than on-land waste collection. In this paper, we propose a two-stage decision-support system to optimize the task allocation and routing decisions for floating debris collection in the reservoir area, where the first stage is proactive planning based on historical/observed data and the second stage is reactive planning based on real-time data. The primary objective is to minimize the total collection cost while simultaneously ensuring the accumulation areas with high risks are prioritized in the daily collection plan, and both genetic algorithm and simulated annealing algorithm are used to solve the optimization problems. The proposed method is validated with a real-world case study at Wushan County in the Three Gorges Reservoir area. The computational results show that the level of time-dependent penalty cost on service priority, the types of collection ships, and the number and locations of unloading points are important influencing factors to the cost and responsiveness. Furthermore, the proposed two-stage decision-support system can help effectively optimize the operational planning of floating debris collection in reservoir areas.

1. Introduction

Floating debris is a pervasive issue across almost all types of water bodies, i.e., streams, rivers, reservoirs, and oceans, though the severity and impact of this problem may vary drastically (Park et al., 2021). Floating debris consists usually of a large variety of substances, e.g., straw, branches, foam, plastics, etc., and they can be found in various locations of the water body. In the case of reservoirs, this problem is mainly caused by the hydrological changes that occur after impoundment, say, the conversion of a natural river channel into a slow-flowing reservoir with a large backwater area results in the accumulation of floating debris that cannot pass through the dam (Zhang et al., 2015). On the Yangtze River, the accelerated accumulation of floating debris has become one of the most significant challenges since the operations of several large water conservancy projects, e.g., Three Gorges Dam and Gezhouba Dam. For instance, the average annual collection volume of floating debris in front of the Three Gorges Dam exceeds 100,000 cubic meters since the impoundment, and the number has dramatically increased to 377,000 cubic meters in 2020.[1]

The floating debris in reservoirs consists of two main sources. One is plant wastes, e.g., plants and straw, and the other is domestic wastes, among which most of them are biodegradable and can thus be value recovered through different recycling processes.[2] During the flood season, a large amount of floating debris can be rapidly accumulated in a very short time, which may not only impose significant risks on waterway transportation but also cause damage to the power generator and dam operations (Wan et al., 2018). Furthermore, the accumulation of floating debris may harm the vulnerable ecosystem and the scenery of the reservoir areas as some of them have become popular tourist destinations, e.g., the Three Gorges Dam. Therefore, the floating debris in the reservoirs needs to be collected and properly treated in a timely and highly responsive way in order to minimize the risks and environmental

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[1] Data source: Environmental Protection Annual Report from 2014 to 2021, Log of the Three Georges Projects Operation from 2003 to 2020. https://www.ctg.com.cn/sxjt/xxxgk/qtxx76/nbxz96/index.html.

[2] Jinghong power station: floating debris into treasure https://www.163.com/dy/article/H85F6LNP0514R9NO.html.

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impacts.

Broadly speaking, the management of floating debris has similar procedures as traditional waste management, which involves waste collection, transportation, processing, recycling, and/or disposal (Akhtar et al. 2017). Waste collection is the initial but costly step of a waste management system (Hoang Lan et al., 2020), and significant research effort has been given to improve waste collection and transportation (Das and Bhattacharyya, 2015; Tirkolaee et al., 2020a; Mahdavi et al., 2022). Even though the other stages for transportation and treatment are similar, the collection of floating debris in reservoir areas differs, however, dramatically from on-land waste collection. First, the changes in water flow and water level over different seasons of the year result in significant dynamicity and uncertainty of the number and locations of the accumulation areas of floating debris. Second, due to the water flow and the weather change of the upper reach, new accumulation areas may appear during the collection, which makes the effective collection of floating debris much more complicated. To tackle this challenge, current research efforts have focused predominantly on providing a better understanding of the characteristics of floating debris and improving the collection equipment and monitoring facilities along the river. However, from the operational planning perspective, no research has been conducted to provide a decision-support system to optimize the use of resources for floating debris collection in reservoir areas under a highly dynamic and uncertain environment.

Therefore, to fill the literature gap, we propose a two-stage decision-support system to optimize the task allocation and routing decisions for floating debris collection in this paper. In the first stage, historical data and/or observed data are used to formulate a proactive plan to assign tasks to collection ships. In the second stage, real-time data collected by the monitoring stations are used to generate reactive planning to deal with new accumulation areas of floating debris in an effective and efficient way. Based on the impact of the floating debris on waterway transportation and dam operations, a time-dependent penalty cost is introduced as a measure to prioritize the collection of some accumulation areas in the daily collection plan. In addition, fuel costs, fixed operating costs of collection ships, and unloading costs are also considered in the model. Furthermore, we incorporate the flow characteristics of the floating debris into the model and set a time window for the collection of different accumulation areas, and the newly emerged accumulation areas during the collection are also considered. The model is derived from a multi-trip dynamic vehicle routing problem with time windows, where a genetic algorithm is used to yield the proactive planning decisions and a simulated annealing algorithm is used for reactive re-optimization. The proposed method is validated with a real-world case study at Wushan County in the Three Gorges Reservoir area to show its applicability and effectiveness.

The remainder of the paper is organized as follows. Section 2 reviews the relevant research and identifies the contributions of the current research. Section 3 introduces the problem and develops the two-stage decision-support system for floating debris collection in reservoir areas. The solution methods are described in Section 4. Section 5 presents a real-world case study, computational results, and discussions. Finally, Section 6 summarizes the paper and gives suggestions for future research.

2. Literature review

In this section, the related research works are reviewed from two aspects: (1) floating debris management in reservoir areas and (2) waste and debris collection problems. Finally, the literature gaps and the contributions of the current research are highlighted.

2.1. Floating debris management in reservoir areas

Floating debris entering reservoirs poses significant environmental challenges and operational risks that require the attention of water resource management worldwide. Its presence may have adverse effects on ecosystems and lead to economic losses (Wan et al., 2018). Previous research has provided comprehensive and valuable insights into the characteristics of floating debris, which laid the foundation for the collection and treatment. For example, based on the analysis of the nature of the floating debris in front of the Three Gorges Dam, Zhang et al. (2020) suggested that, through the proper setup of collection points and the optimized arrangement of reservoir operations, the floating debris collection in reservoir areas can be effectively improved. Park et al. (2021) observed the recurrent distribution of floating debris in numerous artificial lakes within temperate regions during the rainy season, which evaluated the influence of hydrological and meteorological factors, e.g., rainfall and flood characteristics on the distribution of floating debris. Furthermore, Liu et al. (2022) investigated the horizontal and vertical distribution characteristics of microplastics in the Guanyingyan reservoir since the impoundment, which revealed the impact of free-floating plant residues on the distribution of microplastics.

Several studies have been given to adopt new technologies and develop improved equipment and systems for floating debris collection in reservoir areas. For example, Jang et al. (2014) utilized a small tracking buoy equipped with a satellite positioning transmitter to monitor the movement of floating debris in rivers. Gasperi et al. (2014) investigated the quantity and quality of floating plastic debris in the Seine River by employing an extensive network of floating debris retention grids. This approach facilitated the initial assessment of plastic inputs transported by rivers. Qiao et al. (2022) introduced a novel and effective method for detecting floating debris based on YOLOv5 considering the challenges posed by complex lighting conditions, significant scale differences between nearby and distant objects, and the abundance of small-scale floating debris. In summary, existing research predominantly focuses on improving floating debris management efficiency through the investigation of debris properties and the adoption of new technologies in tracking and monitoring the movement of floating debris. However, no research has been conducted to optimize the operational planning of floating debris collection in reservoir areas.

2.2. Waste and debris collection problems

Broadly speaking, the floating debris collection shares many similarities with a vehicle routing problem (VRP), especially for a waste collection system. Considering the dynamicity within the planning horizon, VRP can be categorized into two types, say, static VRP and dynamic VRP (DVRP). In the latter case, the routing decisions are dynamically adjusted. Different variants of VRP have been extensively used for modeling both waste and debris collection problems, which can help generate effective collection planning decisions. For modeling land-based waste collection, e.g., municipal solid waste collection, static optimization models with exact inputs have been widely used in literature (Pillac et al., 2013). For instance, under the smart city concept, Akhtar et al. (2017) investigated a capacitated vehicle routing problem (CVRP) to minimize the overall driving distance in a waste collection system with smart bins. Expósito-Márquez et al. (2019) proposed a waste collection optimization model that aims at maximizing the total amount of collected recyclables, e.g., paper, plastics, etc., in order to minimize adverse environmental impacts. Moreover, several studies took into account the parameter uncertainty, e.g., waste generation (Singh, 2019), and formulated optimization problems with uncertain inputs. For example, Tirkolaee et al. (2020a) developed a robust mixed-integer linear programming (MILP) for municipal solid waste management under demand uncertainty. Bavaghar Zaeimi and Abbas Rassafi (2021) investigated a fuzzy chance-constrained programming model under epistemic uncertainty, say, incomplete data (Tirkolaee et al., 2020b). Hoverer, the major difference between land-based waste collection and the collection of floating debris is related to uncertainty and dynamicity. For the operational planning of urban waste collection,

Table 1
Comparison of the relevant literature.

Literature	Research focus			Type of waste/debris		Decision support		Uncertainty
	Debris features	Collection equipment	Collection planning	Land-based waste/ debris	Water-based debris	Static	Dynamic	
Wan et al. (2018)	√				√ (River)			
Zhang et al. (2020)	√				√ (River)			
Park et al. (2021)	√				√ (River)			
Liu et al. (2022)	√				√ (River)			
Jang et al. (2014)		√			√ (River)			
Gasperi et al. (2014)		√			√ (River)			
Qiao et al. (2022)		√			√ (River)			
Akhtar et al. (2017)			√	√		√		
Expósito-Márquez et al. (2019)			√	√		√		
Singh (2019)			√	√		√		
Tirkolaee et al. (2020a)			√	√		√		√
Bavaghar Zaeimi and Abbas Rassafi (2021)			√	√		√		√
Nickdoost et al. (2022)			√	√		√		
Lorca et al. (2017)			√	√		√		
Duan et al. (2020)			√		√ (Marine)	√		
Tao et al. (2021)			√		√ (Marine)	√		
Duan et al. (2021)			√		√ (Marine)	√		
Our paper			√		√ (River)		√	√

the number and locations of the waste collection points are known before the route is planned, and no collection points will emerge during the collection process, so this problem is usually modeled as a static problem.

Debris collection has been explored for both land-based and water-based waste. The focus of the former type is given to the effective collection and management of debris caused by natural disasters (Nickdoost et al., 2022). The primary aim is to ensure smooth humanitarian operations by minimizing the collection time while maintaining economic effectiveness (Lorca et al., 2017). However, the characteristics of water-based debris are by no means identical. Water-based debris is dynamic, drifting over time due to wind, tides, and currents, and effective collection planning becomes complex. To tackle this challenge, Duan et al. (2020) proposed a route optimization model to minimize the total cost of marine debris collection. Tao et al. (2021) investigated a marine debris collection problem using a heterogeneous collection fleet with different fuels. Duan et al. (2021) combined a wolf pack algorithm with a large neighborhood search to improve the routing optimization for marine debris collection. Using flow characteristics, GNOME was used to predict the movement trajectory of marine debris. These problems were formulated as static VRPs based on the assumption that the locations of the initial debris accumulation areas would remain unchanged if they could be collected within a hard time window. However, in practice, due to changes in water flow, new accumulation areas may dynamically emerge during the collection, Thus, there is a need for new models and decision-support systems that can be used to improve the operational planning of floating debris collection in reservoir areas.

2.3. Literature gaps and contributions of the research

Table 1 presents a vis-à-vis comparison of relevant papers with respect to the type of waste modeled, the planning stages involved, and the uncertainty and dynamicity considered in the planning horizon. As shown in the table, there are three major gaps. First, most previous research focuses either on the characteristics/collection equipment of the debris or on the collection planning of land-based waste or debris, but only a few studies address the challenges of the planning of water-based debris collection. Second, the existing optimization models for water-based debris collection are static and ignore the emergence of new accumulation areas during the collection. However, as dynamicity is one of the most significant features of floating debris, only using the predictive data to determine a fixed collection plan may result in those newly emerged accumulation areas remaining uncollected. Third, previous research primarily addresses marine debris collection planning problems, neglecting the collection of floating debris in river channels and reservoirs. The latter is more sensitive to timeliness and responsiveness. For example, while ships in the ocean can opt for alternative routes to avoid potential collisions with floating debris, such maneuverability is restricted in river channels and reservoirs. The emergence of new debris accumulation zones in these areas poses significantly higher risks. In this regard, the existing optimization models cannot address this challenge to effectively collect the new debris accumulation areas.

To fill the literature gaps, we propose a two-stage decision-support system taking into account the features of floating debris collection in reservoir areas. This two-stage structure is inspired by a data-driven smart logistics management system that has been used in, for example, express delivery (Liu, 2019), where real-time data can be used for re-routing and rescheduling the delivery vehicles for emerging demands under updated time windows. First, proactive planning can be made based on predictive data. During the collection of floating debris, real-time data is used for reactive planning in the second stage, where newly emerged accumulation areas will be dynamically inserted into existing routes in a way that minimizes cost while simultaneously ensuring the updated time windows are met. By adopting this two-stage framework, the aforementioned problems of existing optimization models can be effectively resolved, and the new floating debris accumulation areas that emerged can be collected in an efficient, resource-effective, and responsive manner. Our paper is the first research that uses a two-stage structure to optimize the operational planning of floating debris collection in reservoir areas under a highly dynamic environment. Thus, we aim at making the following contributions:

1. We propose a new two-stage methodological framework that can help with both proactive planning and real-time reactive planning for floating debris collection in reservoir areas.
2. We formulate a new mathematical model that minimizes total collection cost while simultaneously prioritizing the collection of the accumulation areas with higher impact.
3. We validate the proposed decision-support system in real-life scenarios to obtain several generic managerial implications.

3. Methodological development

In this section, the methodological framework of the two-stage decision-support system is first introduced, and a mathematical

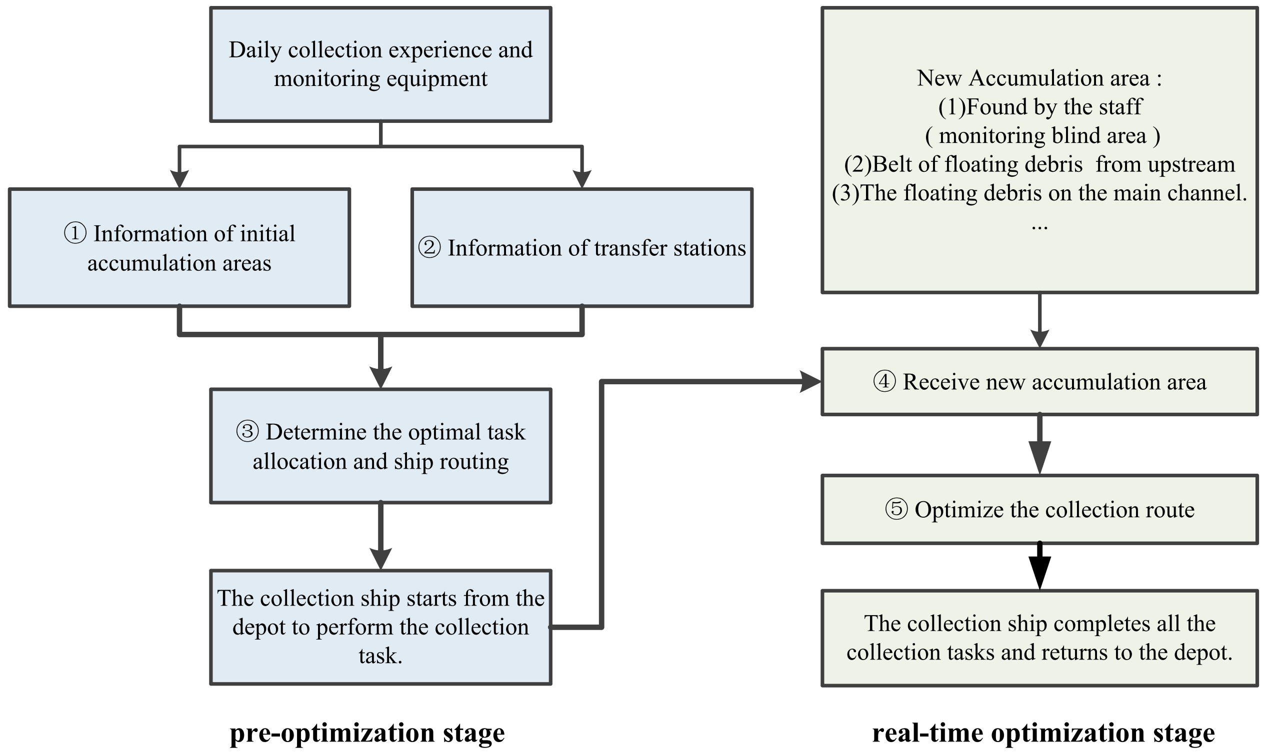

Fig. 1. The collection system of floating debris in reservoir areas.

optimization model is then formulated.

3.1. Methodological framework and assumptions

Due to the dynamicity and uncertainty caused by the changes in water flow and water level, the collection of floating debris is much more complicated than that of urban waste. Furthermore, compared with the floating debris collection in streams and rivers, the collection in reservoirs has its characteristics due to the slow flow velocity (Park et al., 2021). Consequently, the accumulation of floating debris follows a certain regularity, which is typically divided into two types, namely, fixed accumulation areas (static) and flow accumulation areas (dynamic). Most floating debris will be carried by the water flow and will eventually accumulate in the stagnation zone, forming a large accumulation area that needs to be collected in a timely and highly responsive way to minimize the risks to waterway transport and dam operations. In contrast, a small number of accumulation areas will remain in a flow state, which forms belts of floating debris and needs to be collected within a flexible time window. To optimize the collection of floating debris in reservoirs, we propose a two-stage decision-support system including a proactive planning stage and a reactive planning stage, as shown in Fig. 1.

In the first stage, proactive planning is made based on the historical data and the observed data from the monitoring facilities, which forms the daily collection plan for the fixed accumulation areas by determining the optimal task allocation and ship routing. This process aims at minimizing the collection cost and prioritizing the collection of the accumulation areas with a high impact, which helps reduce the risks caused by floating debris accumulation in reservoirs. In the second stage, as new floating debris accumulation areas may emerge during the collection process, reactive planning is made using real-time information. These new floating debris accumulation areas may be due to blind monitoring spots caused by limited capacities or due to the short-term change in water level and water flow. If these floating debris form belts and accumulate near the main channel of waterway transportation, they may yield safety issues and impose significant risks. Thus, the second-stage reactive planning aims at tackling this challenge by re-optimizing the task allocation and ship routing dynamically and effectively with real-time data.

To optimize the floating debris collection plan, we further develop a mathematical model based on a dynamic VRP with time windows, which takes into account the re-optimization of newly emerged accumulation areas during the collection process. In this problem, we consider a fleet with homogeneous collection ships that are dispatched from the depot to a set of floating debris accumulation areas. The trip will start and end at the same deport within the predetermined daily working hours. During the collection process, each collection ship may take multiple tours, and a tour is completed upon the reach of the ship's capacity or upon the completion of the daily collection tasks. The collection ships will upload the floating debris at the nearest unloading points along the river before starting a new tour. In addition, considering effective reactive planning, the ships may need to adapt to changing information, i.e., task assignment and routing, and meet the updated requirement within specified time windows. The objective of the planning is to minimize the total collection cost including the fixed operating cost of the collection ships, fuel consumption cost, and unloading cost, while simultaneously ensuring the effectiveness and responsiveness to collect the floating debris of the accumulation areas with higher priority.

To formulate the mathematical optimization model, the main assumptions of the problem are as follows:

- The fixed floating debris accumulation areas can be determined by historical data and observed data by monitoring facilities.
- During the collection process, the change in the state of the fixed floating debris accumulation areas is negligible and is not taken into account.
- The time windows for each floating debris accumulation area are considered hard constraints.
- The locations of the depot and the unloading points along the river are known.
- The types, the number, and other relevant parameters of collection ships are known or can be estimated.

(A) Mechanical collection ship (B) Manual collection ship

Fig. 2. Collection ship for floating debris at the Three Gorges Reservoir.

- A floating debris accumulation area can only be collected by one ship.
- Euclidean distance is used to calculate the distance matrix.

3.2. *Fuel consumption of the collection ships*

In this paper, we consider a real-world case study of floating debris collection at the Three Gorges Reservoir on the Yangtze River, where two types of collection ships are used, namely, mechanical collection ships and manual collection ships. The mechanical collection ships are used for large accumulation areas, which can transport the floating debris on the river surface to the back cabin using front-end crawlers, as illustrated in Fig. 2(A). The manual collection ships are used for narrow areas such as docks, which rely on the cargo net by collection staff to collect floating debris, as illustrated in Fig. 2(B).

The collection process can be divided into three phases including 1) travel between different locations; 2) collection of floating debris; and 3) unloading operations. During the first phase, the ship moves from one location to another at a certain speed. The speed of the ship determines the amount of fuel consumed per unit of time, with higher speeds leading to increased fuel consumption. In the collection phase, the ship arrives at an accumulation area and collects the floating debris at a low speed. To maintain this low-speed state, the ship requires a certain amount of fuel consumption. Finally, the ship will transport the collected floating debris to the nearest unloading point, where the ship is in a non-working state with little fuel consumption. According to Olmer et al. (2017) and Duan et al. (2020), the fuel consumption during the cruising phase and the collection phases can be estimated by Eq. (1) and Eq. (2), respectively.

$$\text{Fuel consumption per hour during the cruising phase} = \left(\frac{\textit{actual velocity}}{\textit{maximun velocity}}\right)^3 \times (\textit{the fuel consumption per hour at maximum velocity}) \quad (1)$$

In the collection phase, a low speed needs to be maintained. In this paper, to simplify the calculation, Eq. (2) is adopted from Duan et al. (2020), which is used to estimate the carbon emissions of ships in the static state. Notably, the numerator of the first part of the equation may be replaced by the actual speed of collection ships during these operations.

$$\text{Fuel consumption per hour during the collection phase} = \left(\frac{1}{\textit{maximun velocity}}\right)^3 \times (\textit{the fuel consumption per hour at maximum velocity}) \quad (2)$$

Table 2
The sets, parameters, and variables of the mathematical model.

		Description
Sets	$G = (V, A)$	Network of floating debris collection system with nodes V and arcs A
	V	Set of nodes; here, 1 represents the depot,$V = \{1\} \cap N \cap F$
	A	Set of arcs from node i to node j
	N	Set of floating debris accumulation areas,$N = N_s \cap N_d$
	N_s	Set of initial (static) accumulation areas
	N_d	Set of new (dynamic) accumulation areas
	F	Set of unloading stations
	K	Set of drifting ships
	R	Set of trips
	S	An arbitrary set of nodes
Parameters	V_i	Volume of floating debris accumulation area i
	ρ_i	Density of floating debris accumulation area i
	w_i	The weight of the class priority of floating debris accumulation area i
	t_i	Collection time of debris area i or unloading time in the unloading station i
	(e_i, l_i)	Time window of debris area i
	$dist_{ij}$	Length of arc $(i,j) \in A$
	cf_k	Fixed operating cost of collection ship k
	V_k	The volume capacity of collection ship k
	W_k	The weight capacity of collection ship k
	T_k	Maximum daily working time for collection ship k
	v_k	Cruising speed of collection ship k
	v_k^{max}	Maximum speed of collection ship k
	b_k	Fuel assumption per hour of collection ship k at maximum speed
	f_k	Unit fuel consumption cost of collection ship k
	fd_i	Unloading cost in unloading station i
	fr_i	Fixed facility cost in unloading station i
	M	A very large number
Decision variables	x_{ijkr}	1 if node j is visited after node i by ship k in trip r;0 otherwise
	y_k	1 if ship k is used in the day;0 otherwise
	z_i	1 if unloading station i is used in the day;0 otherwise
Auxiliary variable	AT_i	Arrival time at floating debris accumulation area i

3.3. *Service priority*

In the daily collection at the Three Gorges Reservoir, the accumulation areas of floating debris are categorized into four levels of service priorities based on their impact. The first priority is given to areas that yield a significant impact on the quality of domestic water, e.g., the water source for residential areas. The second priority is given to locations that have a significant impact on the navigation safety of reservoir areas, e.g., ports and main channels of waterway transport. The third priority is given to areas that affect the ecosystem and scenery of the reservoir area, and the least priority is given to the other areas.

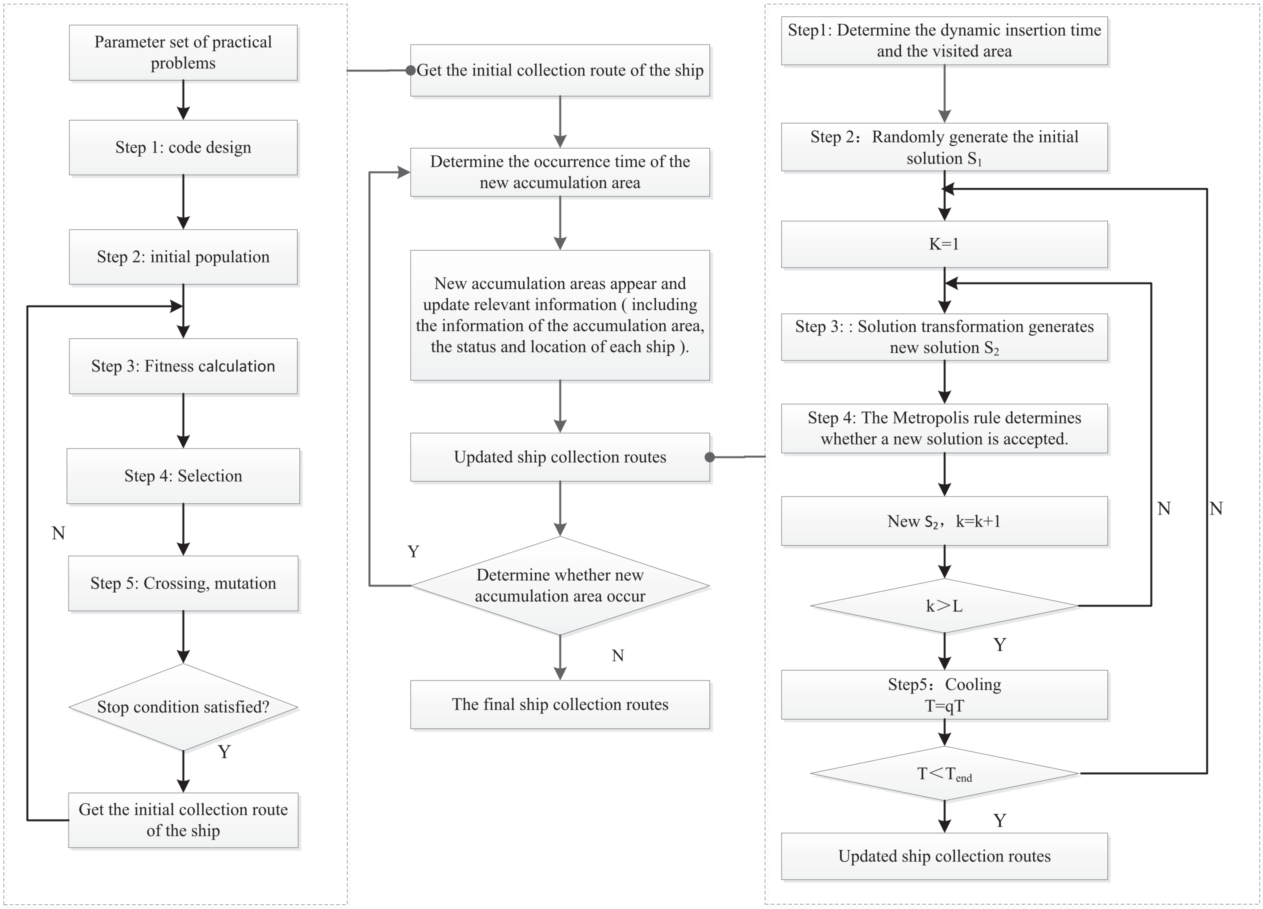

Fig.3. Two-stage solution strategy.

To model the impact of different levels of service priority, we use a time-dependent penalty cost in this paper. Specifically, we introduce a penalty cost function for each accumulation area, as shown in Eq. (3), which is directly proportional to both the weight of service priority w_i and the service start time AT_i. Furthermore,X_i is introduced to monetize and convert the product of w_i and AT_i into a penalty cost. The weight of each point is determined by its service priority level, with higher levels assigned higher weights. This prioritization ensures that areas with the highest service priority are collected first. To determine the weights of each service priority level, we use the method derived from Perrier et al. (2007) and Ahabchane et al. (2021). Besides, the pairwise comparison is used to allocate weight to each service priority level, and as argued by many, this method can provide a relatively accurate trade-off comparison among different criteria. The proposed time-dependent penalty cost provides a practical approach to incorporate the service priority into the collection planning of floating debris in a way that minimizes the risks and impact.

$$\Gamma(i) = X_i AT_i w_i \tag{3}$$

3.4. Set, parameters, and variables

The sets, parameters, and variables used in the model formulation are first given in Table 2.

3.5. Mathematical model

The objective function is given in Eq. (4), which minimizes the total cost of floating debris collection in reservoir areas. The first part is the fixed operating costs of collection ships, and the second and third parts calculate the fuel consumption costs in different stages. The fourth and fifth part is the unloading and fixed facility costs of unloading stations, and the last part is the time-dependent penalty cost of service priority.

$$\begin{aligned} \text{minimize } Z = & \sum_{k\in K} y_k cf_k + \sum_{i\in V}\sum_{j\in V}\sum_{k\in K}\sum_{r\in R}\frac{f_k b_k dist_{ij}}{\left(v_k^{\max}\right)^3}(v_k)^2 x_{ijkr} + \sum_{i\in N}\sum_{j\in N}\sum_{k\in K}\sum_{r\in R}\frac{f_k b_k t_i}{\left(v_k^{\max}\right)^3} x_{ijkr} + \sum_{j\in V}\sum_{i\in F} x_{jikr} fd_i \\ & + \sum_{i\in F} z_i fr_i + \sum_{i\in V} X_i AT_i w_i \end{aligned} \tag{4}$$

S.t.

$$\sum_{j\in N} x_{ijkr} = \sum_{j\in N} x_{jikr} \quad \forall i\in V; i\neq j, k\in K, r\in R \tag{5}$$

$$\sum_{i\in V}\sum_{r\in R}\sum_{k\in K}x_{ijkr} = 1 \;\forall j\in N; i\neq j \tag{6}$$

$$\sum_{i\in V}\sum_{j\in N}V_j x_{ijkr} \leq V_k \forall k\in K, r\in R \tag{7}$$

$$\sum_{i\in V}\sum_{j\in N}\rho_j V_j x_{ijkr} \leq W_k \forall k\in K, r\in R \tag{8}$$

$$\sum_{i\in V}\sum_{j\in V}\sum_{r\in R}\frac{dis_{ij}}{v_k}x_{ijkr} + \sum_{j\in N\cap F}\sum_{r\in R}t_j x_{ijkr} \leq T_k \;\forall k\in K \tag{9}$$

$$AT_j - \sum_{i\in V}\sum_{k\in K}\sum_{r\in R}M\left(1-x_{ijkr}\right) \leq \sum_{i\in V}\sum_{k\in K}AT_i + t_i + \frac{dis_{ij}}{v_k} \leq AT_j + \sum_{i\in V}\sum_{k\in K}\sum_{r\in R}M\left(1-x_{ijkr}\right) \;\forall j\in N \tag{10}$$

$$AT_1 = 0 \tag{11}$$

$$e_i \leq AT_i \leq l_i, i\in N \tag{12}$$

$$\sum_{j\in N}x_{1jk1} = y_k \;\forall k\in K \tag{13}$$

$$\sum_{j\in N}\sum_{i\in F}x_{jik1} = y_k \;\forall k\in K \tag{14}$$

$$\sum_{i\in F}\sum_{j\in N}x_{ijkr} \leq y_k \;\forall k\in K, r\in R\{1\} \tag{15}$$

$$\sum_{j\in N}\sum_{i\in F}x_{jikr} \leq y_k \;\forall k\in K, r\in R\backslash\{1\} \tag{16}$$

$$\sum_{i\in F}\sum_{r\in R}x_{i1kr} = y_k, \forall k\in K \tag{17}$$

$$\sum_{i\in S}\sum_{j\in S\, i\neq j}x_{ijkr} \leq |S|-1 \quad \forall S\in V\backslash\{1\}\cup F; S\neq\varnothing, k\in K, r\in R \tag{18}$$

$$x_{ijkr}, y_k \in \{0,1\}, \forall i,j\in N, k\in K, r\in R \tag{19}$$

$$z_i \in \{0,1\}, \forall i\in F \tag{20}$$

$$AT_i \geq 0, \forall i\in V \tag{21}$$

The model is restricted by constraints (5–21). Eq. (5) is the flow balance constraint for each accumulation area. Eq. (6) guarantees that each accumulation area will be served by only one collection ship. These two equations require that all the floating debris accumulation areas in the reservoir area will be collected. Constraints (7) and (8) are capacity constraints, which ensure the volume and weight limitations of the collection ship cannot be exceeded on each tour. Constraint (9) sets up the upper limits of working time for the collection ships. Constraints (10) and (11) calculate the service start time of each accumulation area. Constraint (12) sets up the time window for each accumulation area. Constraints (13) and (14) require that a collection ship starts the first tour from the deport and completes it at an unloading point along the river. Besides, they also ensure that a tour can be performed by collection ship k only when it is selected. Constraints (15) and (16) indicate that a collection ship may perform another tour when completing the first tour. Constraint (17) guarantees that all the selected collection ships will complete their last tour and return to the depot. Constraint (18) eliminates any possible sub-tours. Constraints (19)-(21) set the domains of variables.

4. Solution approach

To solve the optimization problem, we propose a two-stage solution strategy for optimizing the task allocation and route of a collection ship. The first stage is pre-optimization based on the historical/observed data of the floating debris accumulation area, where a genetic algorithm (GA) is used to solve the collection ship routing problem and to yield the initial collection plan. In the second stage, real-time reactive optimization is performed to better deal with the dynamic demand. There are two types of real-time optimization approaches, namely, periodic re-optimization and continuous re-optimization (Pillac et al., 2013). Based on the characteristics of the problem, continuous re-optimization is chosen, which can help effectively and efficiently insert new accumulation areas into the appropriate paths. Specifically, we use the moment of appearance of new accumulation areas for insertion and for replanning the collection path using the simulated annealing algorithm (SAA), as illustrated in Fig. 3.

(1) GA for pre-optimization

Step 1: Chromosome representation

Given the specific structure of the collection ship routing problem, we use the natural sequence as the coding of the chromosome. The chromosome coding $n+m+1$ corresponds to the network of n floating debris accumulation areas that need to be collected by m ships.

Step 2: Population initialization

After completing the chromosome coding, we generate an initial population by randomly selecting n collection areas and adding 1 to the starting and ending depots (represented as 1), e.g., $(1, i_1, i_2, \cdots i_e, 1)$. With the load constraints, $\sum_{i-1}^{e}q_i$ is calculated. If $\sum_{i-1}^{e}q_i \leq Q$ and $\sum_{i-1}^{e+1}q_i > Q$, 0 is inserted between the i_e area and the i_{e+1} area. Otherwise, moving a region forward or backward for a new insertion. For collection ships with time windows, t_i is calculated. If $ET_i \leq t_i \leq LT_i$, insert 0 into the i_i region. Otherwise, a new insertion is needed. This is repeated until enough racial groups are produced. This process is repeated until enough individuals are generated.

Step 3: Fitness evaluation

The fitness function is determined by the objective function, with which the fitness value of the individual population can be calculated. Since the objective function of this paper is for minimum cost, we evaluate the fitness of each individual in the population using the reciprocal of Eq. (4). The optimization goal is to select the chromosome with the highest fitness value.

Step 4: Selection

To select individuals from the population for the next generation, we employ the 'roulette' method, which involves assigning a selection probability to each individual proportional to its fitness value. This allows individuals with higher fitness values to have a greater chance of being selected for reproduction and ensures that the population evolves towards better fitness values over time.

Step 5: Crossover and mutation

Crossover and mutation operations are performed on the selected individuals to generate new subpopulations. We use the Position-Based Crossover (PBX) method to exchange partial genes of paired individuals, and the exchange variation method to swap two randomly selected clients' positions.

Step 6: Stopping condition

In this paper, the maximum number of iterations is used as the stopping criterion. When the number of iterations reaches the preset limit, the iteration is terminated to output the optimal solution obtained. Otherwise, we return to Step 4.

(2) SAA for re-optimization

Step 1: Determine the dynamic accumulation areas during the collection.

The pre-optimization determines the initial resource allocation and routing for floating debris collection. However, new accumulation areas may be generated during the collection, whose information can be collected by the real-time monitoring system. The time and location of

Table 3
Optimality gaps and computational performance.

Case	Optimality gap	Computational performance		
		Solution time Gurobi (s)	Solution time DSS (s)	Gap
1	0.15 %	79.61	4.17	94.76 %
2	0.25 %	103.07	4.30	95.83 %
3	0.34 %	129.88	4.49	96.54 %
Average	0.25 %	104.19	4.32	95.85 %

the new accumulation areas provide information for the re-optimization based on the existing collection plan and resource availability.

Step 2: Initial Solution.

At the initial temperature, a random initial feasible solution S_1 is generated, and the objective value is calculated as $f(S_1)$.

Step 3: Solution transformation.

A new solution is generated by transforming the current solution. In this case, a random number is used to select two accumulation areas to be exchanged. The two-neighborhood change method is used to generate a new feasible solution S_2, and the objective function value is then calculated as $f(S_2)$.

Step 4: Metropolis rule.

The difference between the two obtained solutions can be calculated by $df = f(S_2) - f(S_1)$, and the Metropolis criterion is then given as: $P = \begin{cases} 1, & df < 0 \\ \exp\left(-\frac{df}{T}\right), & df \geq 0 \end{cases}$. If $df < 0$, S_2 is accepted with the probability of 1 as the new feasible solution. Otherwise, the acceptance probability of S_2 is calculated by generating a random number from a uniform distribution interval (0, 1). If $\exp\left(-\frac{df}{T}\right) > \text{rand}$, S_2 is accepted as a new feasible solution. Otherwise, the current solution S_1 is kept.

Step 5: Cooling down.

The cooling rate q is used to reduce the temperature, say $T = qT$. If T is less than the end temperature, the iteration stops and the current optimal result obtained is outputted for the re-optimization plan. Otherwise, the iteration continues.

5. Computational experiment and case study

In this section, we perform a computational experiment to verify the method and a real-world case study at the Three Gorges Reservoir area to validate and to show the effectiveness and applicability of the proposed two-stage decision-support system.

5.1. Computation performance of the DSS

To verify the performance of the solution approach applied, we test the algorithm with three small-scale problem instances and compare the results with that obtained by a commercial optimization solver Gurobi. We randomly generated the parameters for three test cases with 10 accumulation areas. The computations are performed with both Gurobi and MATLAB 2019a on a computer with Inter Core i5-7200U CPU and 4 GB RAM. The parameters of both GA and SAA were initially set up based on Moon et al. (2012), Bae and Moon (2016), and Tirkolaee et al. (2019). Then, we systematically compared and evaluated these test parameters in order to select the best combinations for our experiment. The evaluations of both GA and SAA are provided in Appendix A (Tables A1 and A2). Based on the evaluation result, the parameters for GA were set as follows: $NP = 80, P_c = 0.9, P_m = 0.1$, and $maxgen = 800$. The parameters for SAA were set as follows:$q = 0.98$, $T = 1000$, $T_{end} = 0.00001$, and $L = 5$. Table 3 shows the optimality gap and computational comparison. As can be seen, for the three test cases, the computational time can be reduced by 94.76 %, 95.83 %, and 96.54 %, respectively, compared with that using Gurobi. Thus, the proposed solution can obtain highly confident solutions with much shorter computational times required.

5.2. Case study of three gorges reservoir area

To show the applicability and effectiveness of the proposed DSS, we then performed a case study at the Three Gorges Reservoir area. Since the commencement of water storage and power generation of the Three Gorges Dam in 2003, the management of floating debris in the reservoir area has become a significant challenge. To tackle this issue, several collection points have been set up by the counties and municipalities along the Yangtze River, as shown in Fig. 4. The Three Gorges Reservoir area spans across Hubei and Chongqing. Based on the existing collection points and facilities, a monitoring network has been established along

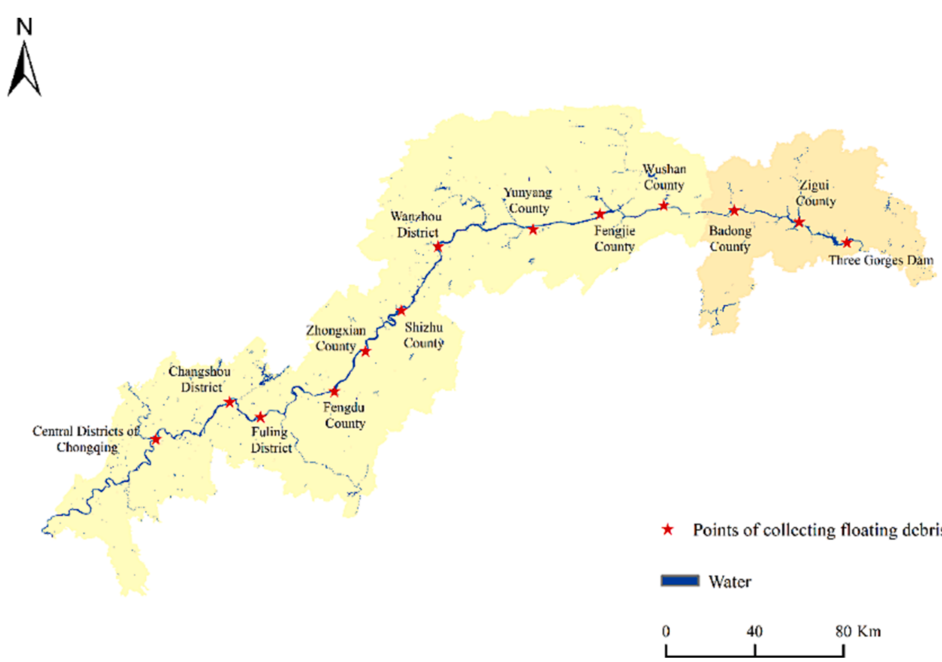

Fig.4. Collection points of floating debris along the Yangtze River.

the mainstream of the Yangtze River, which effectively covers a 660 km water surface between Jiangjin and the Three Gorges Dam. The monitoring network enables the timely and accurate identification of the location and movement of floating debris on the water surface, which provides essential information to guide the collection of floating debris at each location.

Located at the end of the Yangtze River in Chongqing, Wushan County serves as the last collection point of floating debris in this region. Wushang County is responsible for managing the collection of 183.45 km of water surface in the mainstream and tributaries of the Yangtze River. This makes Wushan County a critical line of defense against floating debris entering the downstream Three Gorges Reservoir area. Given its important geographical location, it is imperative to improve the effectiveness and efficiency of floating debris collection in Wushan County. Therefore, in this paper, the proposed two-stage decision-support system is used to optimize and improve the planning of collection operations of floating debris in Wushan County.

5.3. Data and parameters

With support from the Three Gorges Group, the Hydrological Bureau, and the local governments of the relevant counties in Chongqing, our research group conducted fieldwork on the collection points located in front of the Three Gorges Dam and in Wushan and Fengdu Counties in 2021. During this fieldwork, real-world data and information associated with collection ships and floating debris accumulation areas were collected, based on which the two-stage decision-support system is tested and validated.

Data on floating debris accumulation areas were collected in October 2021 during the water storage period of the Three Gorges Reservoir. At this time, the water level was high at 175 m, resulting in mostly still water with a low flow rate of around 0.3 m/s. The distribution of floating debris was significantly impacted by wind, resulting in several clustered floating debris accumulation areas dispersed across the main channel of the Yangtze River. The density of floating debris ranged from 0.16 to 0.26 g/cm^3. As a key monitoring point of floating debris in the Three Gorges Reservoir Area, 360-degree rotating 'Global Eye' HD cameras are used in Wushan County to provide both fixed-point observation and dynamic inspection. The distribution of initial accumulation areas is shown in Fig. 5, with detailed information provided in Table 4. In addition, in order to test the performance of the decision-support system, five new accumulation areas are randomly generated for the reactive planning stage, whose information is provided in Table 5.

Limited by the water level conditions, only three locations in this section of the Yangtze River can be used as unloading points during the experimental period, which are 34, 35, and 36 in Table 6. In addition, it is noteworthy that 34 is also the deport of collection ships, as shown in Fig. 5. Table 7 summarizes the parameters of the collection ships, which were obtained from literature research or from the shipbuilders' websites. In this case study, we only considered the use of mechanical collection ships. In the Three Gorges Reservoir Area, all mechanical collection ships are powered by diesel. The average diesel price in Chongqing during the study period (8.53 CNY/L) was thus used in our experiment. Given the particularity of the floating debris collection and to reduce safety risks for the staff working on the river, a working time limit of 6.5 h per day was imposed for all the collection ships, say, $T_k = 6.5 (k \in K)$

5.4. Experimental results

Based on the given data and information, the daily collection plan of floating debris is optimized. As can be seen, five collection ships are selected, whose routes, collection weights and volume, and total travel distance and working time in both the proactive stage and the reactive stage are given in Table 8. When solving this problem with a single-stage model based only on predictive data, these new accumulation areas may remain uncollected. Otherwise, more resources may be allocated to ensure timely debris removal. For comparison purposes, we also solved the same problem with a static single-stage approach. When new accumulation areas emerge, the GA is run to generate additional routes for collecting the floating debris in these points. In comparison to the optimal solution derived from the two-stage decision-support system, the overall collection cost rises by 1.26 %, necessitating an additional collection ship.

5.5. Sensitivity analysis

In this section, we conduct sensitivity analysis by varying the weight of service priority, the type of collection ship, and the number of unloading stations.

5.5.1. The level of penalty cost on service priority

In this paper, in order to prioritize the accumulation areas that may yield significant impacts, a time-dependent penalty cost is formulated, where X_i is used to convert the weighted priority level into a penalty cost in the objective function. Thus, the value of X_i determines the impact of the priority level in the daily collection planning. In the numerical experiments, we evaluated five different scenarios to better understand the impact of the changing level of penalty cost on decision-making, where $X_i = 0$, $X_i = 10$, $X_i = 100$, $X_i = 1000$, and $X_i = 10000$ were implemented.

Fig. 6 shows the change of the starting time of collection at different priority groups. As the level of penalty cost on service priority increases,

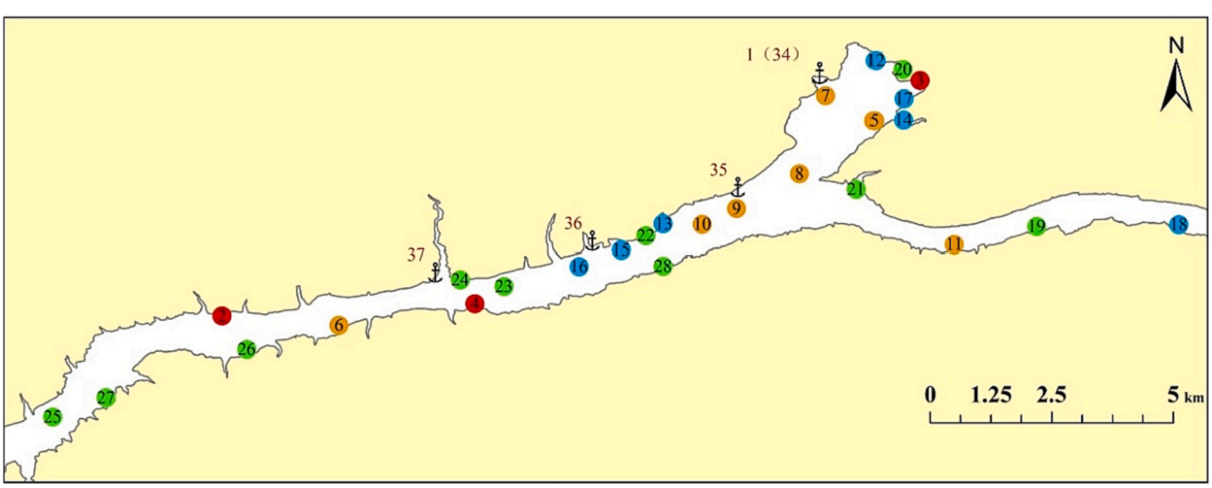

Fig.5. The collection area of floating debris in Wushan County.

Table 4
Initial accumulation areas of floating debris based on observed data.

Debris No.	Latitude (N)	Longitude (E)	Volume (m^3)	Weight (ton)	Window times	Collection time (h)	Service priority
1	**109.8984**	**31.0897**					
2	109.7798	31.0492	28.8742	6.6411	[7:00AM,13:30AM]	0.40	A
3	109.9072	31.0913	25.4628	5.8564	[7:00AM,13:30AM]	0.45	A
4	109.8334	31.0406	15.0286	3.3063	[7:00AM,13:30AM]	0.65	B
5	109.9013	31.0828	22.8594	5.0291	[7:00AM,9:00AM]	0.50	B
6	109.8016	31.0447	24.5411	5.3990	[7:00AM,9:00AM]	0.55	B
7	109.8912	31.0878	17.9137	3.9410	[7:00AM,13:30AM]	0.60	B
8	109.8864	31.0734	14.8792	3.1246	[7:00AM,13:30AM]	0.70	B
9	109.8760	31.0665	16.6231	3.8233	[7:00AM,13:30AM]	0.65	C
10	109.8684	31.0641	21.0405	4.8393	[7:00AM,13:30AM]	0.45	C
11	109.9270	31.0760	32.0342	6.7272	[7:00AM,13:30AM]	0.55	C
12	109.8966	31.0997	28.1882	5.9195	[7:00AM,9:30AM]	0.40	C
13	109.8612	31.0642	41.8243	10.0378	[7:00AM,13:30AM]	0.80	C
14	109.9192	31.0918	48.5277	11.6467	[7:00AM,13:30AM]	0.75	C
15	109.8517	31.0629	31.5265	7.2511	[7:00AM,13:30AM]	0.30	D
16	109.8469	31.0593	42.1197	9.2663	[7:00AM,13:30AM]	0.35	D
17	109.9352	31.0912	39.1896	8.2298	[7:00AM,9:00AM]	0.40	D
18	109.9563	31.0640	13.9231	3.0631	[7:00AM,13:30AM]	0.45	D
19	109.9307	31.0621	22.8231	5.2493	[7:00AM,13:30AM]	0.55	D
20	109.9130	31.0972	13.0246	2.9957	[7:00AM,13:30AM]	0.35	D
21	109.9084	31.0744	21.8285	5.0206	[7:00AM,13:30AM]	0.30	D
22	109.8580	31.0620	27.4284	6.3085	[7:00AM,13:30AM]	0.40	D
23	109.8318	31.0528	19.8552	4.3681	[7:00AM,13:30AM]	0.35	D
24	109.8252	31.0561	18.2925	4.2073	[7:00AM,13:30AM]	0.30	D
25	109.7486	31.0287	17.5487	3.8607	[7:00AM,13:30AM]	0.40	D
26	109.7870	31.0371	21.8749	4.8125	[7:00AM,13:30AM]	0.40	D
27	109.7629	31.0132	18.7759	4.1307	[7:00AM,13:30AM]	0.25	D
28	109.8628	31.0541	19.6874	4.1344	[7:00AM,9:00AM]	0.45	D

Table 5
New accumulation areas of floating debris in the experiment.

Debris No.	Latitude (N)	Longitude (E)	Volume (m^3)	Weight (ton)	Window times	Collection time (h)	Service priority
29	109.8628	31.0541	11.5222	2.6501	[9:00AM,11:00AM]	0.15	B
30	109.8046	31.0447	17.2896	3.6308	[10:00AM,12:00AM]	0.30	D
31	109.9174	31.0597	13.6511	3.0032	[10:30AM,12:30AM]	0.25	D
32	109.9034	31.0866	15.7115	3.6136	[11:00AM,13:00AM]	0.30	B
33	109.8836	31.0639	9.4847	1.9918	[11:30AM,13:30AM]	0.15	D

Table 6
Unloading points.

Debris No.	Latitude (N)	Longitude (E)	Unloading time (h)	Unloading cost/ gate fee (CNY/ time)	Fixed facility cost (CNY/ day)
34	**109.8984**	**31.0897**	**0.3**	**100**	**0**
35	109.8766	31.0667	0.3	100	100
36	109.8497	31.0564	0.3	100	200
37	109.8224	31.0515	0.3	100	300

Table 7
Parameters of the mechanical collection ship.

parameter	value
Weight capacity	39.6 ton
Volume capacity	98 m^3
Maximum velocity	30 km/h
Cruising velocity	25 km/h
Working time limit	6.5 h/day
Fixed operating cost	1800 CNY
Fuel consumption at max velocity	120 L/h

all accumulation areas in priority class 1 and most accumulation areas in priority class 2 (except 30 and 32) are assigned to earlier time slots for floating debris collection. In contrast, the starting times of floating debris collection at several accumulation areas in priority groups 3 and 4 need to be adjusted and delayed accordingly with respect to the overall capacity limitation. When the priority level is not taken into account in the optimization model (X_i=0), the collection of all the floating debris accumulation areas in priority class 1 is completed at 11:41. However, when *Xi* increases, the completion time of floating debris collection in this group becomes progressively earlier, e.g., at 8:31when$X_i = 100$, and it can be further improved to 7:53 when$X_i = 10000$. This result explicitly shows the impact of the changing level of penalty cost on the planning of floating debris collections.

On the other hand, when a higher level of penalty cost on service priority is imposed, both collection cost and total travel distance are increased, as shown in Fig. 7. When$X_i = 0$, the optimization primarily focuses on efficiency by minimizing the overall collection cost, but the responsiveness to the accumulation areas with high priority (2, 3, and 4) becomes however very low, which may lead to significant risks related to navigation safety and ecological system at the Three Gorges Reservoir area. When the penalty cost on service priority is considered, the optimization model balances the trade-off between the overall collection cost and the responsiveness to the accumulation areas with high priority. For example, when$X_i = 100$, the completion time of collecting all floating debris areas in priority group 1 can be reduced by 2.17 h, but the collection cost and total travel distance will be increased by 1.7 % and 2.68 %, respectively. Therefore, our experimental results suggest that an appropriate level of penalty cost on service priority needs to be determined considering the trade-off between the cost and the responsiveness.

Table 8
Summary of initial collection routes and updated collection routes of collection ships.

	Ship No	Collection route	Collection volume (m^3)	Collection weight (t)	Collection distance (km)	Collection time (h)
Initial collection route	1	1-2-12-19-18-**34**-22-**34**-1	121.237	27.182	48.432	4.737
	2	1-10-20-28-27-**34**-25-14-**34**-1	138.605	31.607	77.924	6.367
	3	1-3-21-5-7-**34**-11-24-26-**34**-1	160.266	35.594	35.111	5.104
	4	1-17-8-9-**34**-16-15-34-23-**34**-1	164.193	36.063	40.187	5.257
	5	1-4-6-13-**34**-1	81.394	18.743	21.933	3.177
Updated collection route	1	1-2-12-19-18-**34**-14-**34**-33-**34**-1	151.821	34.511	48.957	5.558
	2	1-10-20-28-27-26-**34**-31-32-**34**-1	123.766	27.529	50.258	5.060
	3	1-3-21-5-7-**34**-15-16-25-**34**-1	179.259	40.225	37.446	4.998
	4	1-17-8-9-**34**-11-22-23-**34**-1	150.010	32.582	33.286	4.981
	5	1-4-6-13-**34**-29-30-24-**34**-1	128.498	29.231	43.033	5.071

5.5.2. *The type of collection ships*

Our numerical experiment focuses on optimizing the collection of floating debris in the Three Gorges Reservoir areas using a homogeneous fleet, meaning that all ships have the same capacity. While different types of ships may be used to perform this task, selecting appropriate types of collection ships becomes thus important to minimize the total cost. For instance, a larger ship may be able to collect more accumulation areas within the time window, but a higher fixed operating cost will usually be incurred as well. Therefore, in this section, we compare 8 different types of collection ships in order to better understand the impact of using different types of collection ships on floating debris collection at the Three Gorges Reservoir area. The detailed information is given in Table 9, where B4 was used in the previous numerical experiments.

When the floating debris is collected by B1 and B2, a minimum of 6 ships are required due to their small capacities. While using the other types of collection ships, only 5 are needed to complete the same tasks. However, it is noteworthy that the number of unloading operations decreases from 14 to 9 with the increase of ship capacity from B1 to B8. Fig. 8 depicts the change in the collection cost and the time-dependent penalty cost by using different collection ships. The results demonstrate that, as the ship capacity increases, the collection cost initially decreases before reaching the minimum value at B5 and then increases. The lowest collection cost is 14865.31 CNY, representing an 8.9 %

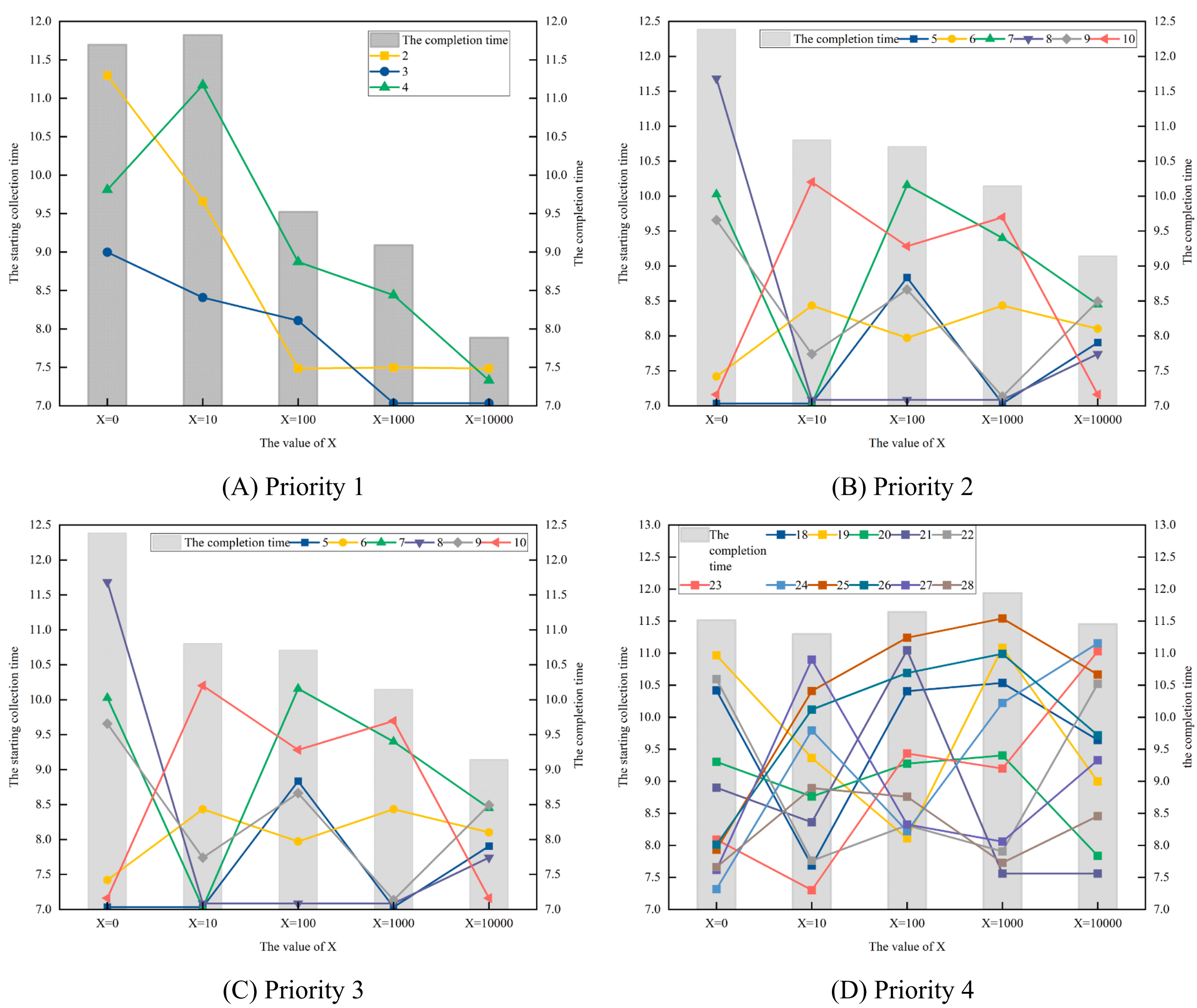

Fig. 6. The change of the starting time of collection at different priority groups.

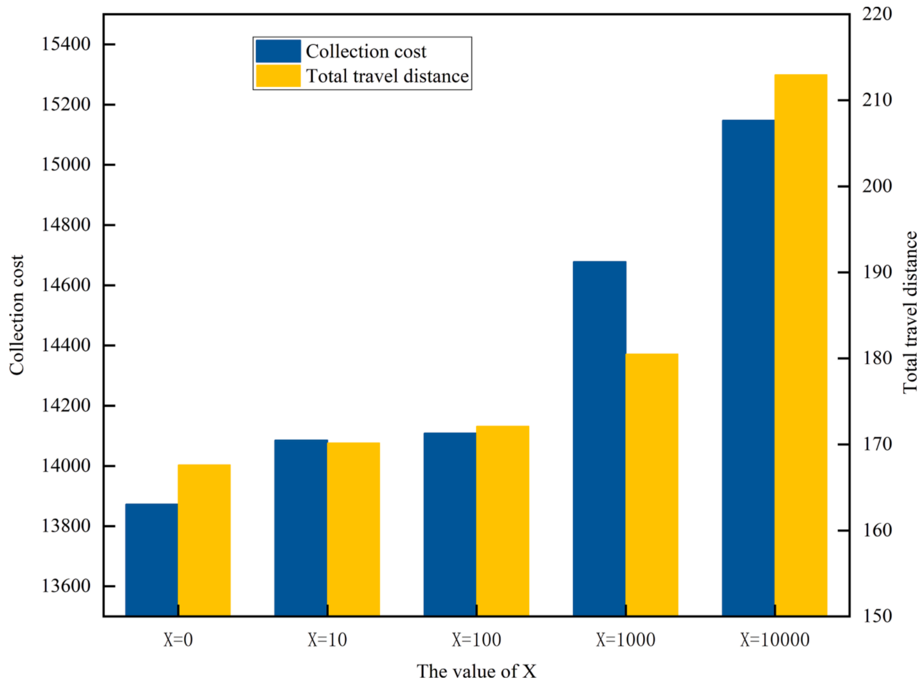

Fig 7. The impact of the changing level of penalty cost on the collection cost and total travel distance.

reduction compared to the highest cost observed for ship type B1. On the other hand, the analysis shows that the time-dependent penalty cost decreases as the ship capacity increases, where using ship type B8 shows a 1.59 % reduction compared with that of ship type B1. The underlying reason is that increasing the ship capacity does not change the collection sequence of the accumulation areas with the highest priority. However, the collection time of accumulation areas with lower priority becomes earlier due to the reduced trips to unloading points, which results in a reduction of the time-dependent penalty cost.

Finally, the experimental results indicate that using larger collection ships may help reduce the total collection time and minimize the number of unloading operations, but a higher cost will likely be incurred. However, on the other hand, using collection ships with insufficient capacity, e.g., B1 and B2 in this case, will not only increase the unloading operations and the total collection time but also yield a high cost. Due to these reasons, our experimental results suggest that selecting the appropriate types of collection ships is of significant importance for floating debris collection in reservoir areas.

5.5.3. The number of unloading points

The collection area for floating debris in reservoir areas is usually characterized by a long and narrow river surface with a long river bank. Apart from the main unloading point located at the depot, several ports along the river can serve as temporary unloading stations, in which case an additional gate fee may be incurred for their use. The information related to these unloading points has been given previously in Table 4, where using a temporary unloading point will incur a higher cost than using the deport. The selection of temporary unloading points may drastically affect the cost, working time, and travel distance of floating debris collection. To better understand this impact, we analyze 8 scenarios with the different combinations of unloading points, as shown in Table 10.

Table 9
Different types of mechanical collection ships.

Type	Volume capacity (m^3)	Weight capacity (t)	Fixed operating cost (CNY)
B1	83	33.4	1500
B2	88	35.3	1600
B3	93	37.3	1700
B4 (Base case)	**98**	**39.6**	**1800**
B5	103	41.2	1900
B6	108	42.1	2000
B7	113	45.1	2100
B8	118	47.7	2200

It can be seen from Fig. 9(A) that, in general, increasing the number of unloading points can help reduce the total travel distance of the collection ships. From Fig. 9(B), it is also noteworthy that using more unloading points will help improve the responsiveness of the floating debris collection, which is measured by the time-dependent penalty cost. Furthermore, the location of the unloading points plays a crucial role in the travel distance, the total collection cost, and the responsiveness, as shown in Fig. 9. For instance, when two unloading points are used, the total travel distance, the total collection cost, and the responsiveness can be improved in scenarios S2 and S3 compared with that of the one unloading point scenario (S1). This is because collection ships can find a closer location to upload the floating debris in these two scenarios. However, when unloading points 34 and 37 are used in scenario S4, an increase in both total travel distance and total collection cost can be observed. This is mainly due to the remote location of unloading point 37. In the optimal solution, which balances the trade-off between both cost and responsiveness, this location is used in several tours to ensure the responsiveness of the floating debris collection, say, maintaining a lower time-dependent penalty cost in the objective function. However, this will increase the total travel distance and total collection cost. A similar phenomenon is also observed in scenarios S6, S7, and S8 when unloading point 7 is used. In scenario S8, it is obvious that the responsiveness is maximized when four unloading points are used, but the total travel distance is increased. This leads to the highest total collection cost among all scenarios. Besides, the increasing fixed facility cost when more unloading points are used may also be an explanation for the cost increments in this scenario. Our experimental results suggest that selecting the appropriate number and location of unloading points may yield a significant impact on the total travel distance, total cost, and responsiveness of the optimal planning of floating debris collection.

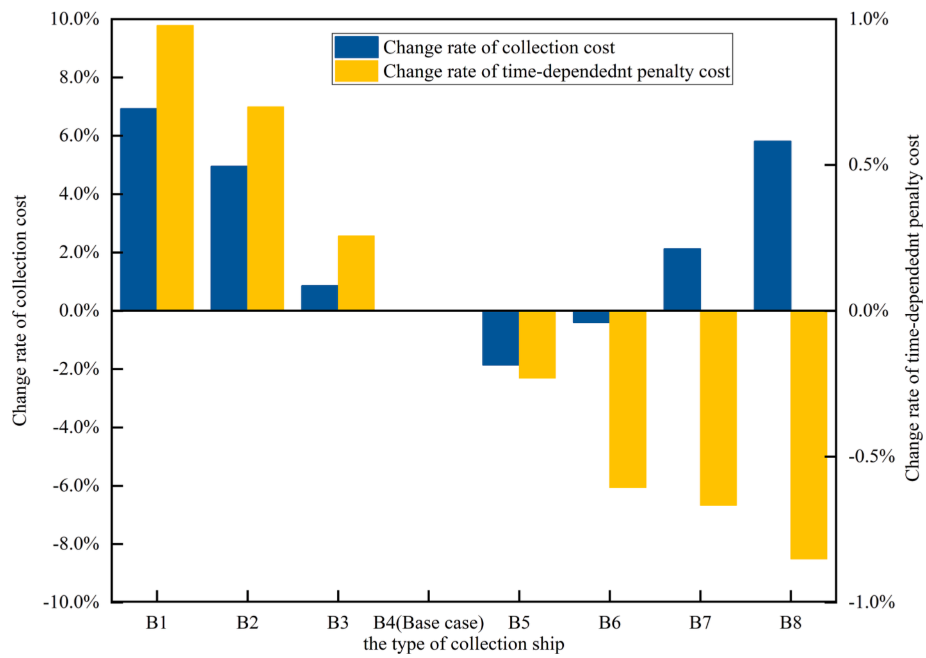

Fig. 8. Change of collection cost and time-dependent penalty cost with different types of collection ship.

Table 10
Different combinations of unloading points.

Number of unloading points	Scenarios	Uploading points used
1	**S1 (Base case)**	**34**
2	S2	34.35
	S3	34.36
	S4	34.37
3	S5	34.35.36
	S6	34.35.37
	S7	34.36.37
4	S8	34.35.36.37

6. Conclusions

One of the main challenges led by water conservancy projects is the accumulation of floating debris in the reservoir area. On the one hand, floating debris is considered a type of waterborne waste that has a high recycling value. On the other hand, however, if the floating debris cannot be collected in an effective and timely manner, a significant threat will be posed to waterway transportation, dam operations, and the water environment and overall ecological system in the reservoir area. Consequently, the influx of floating debris into reservoirs has emerged as a crucial environmental concern requiring global attention in water resources management. In this paper, we propose a two-stage decision-support system for floating debris collection in reservoir areas, which optimizes both proactive planning and reactive planning in respective stages. A new mathematical model is formulated to minimize the total collection cost of floating debris collection within a given planning horizon while, at the same time, prioritizing the collection of accumulation areas that may yield more significant environmental and safety impacts. To model and deal with the dynamicity and uncertainty of the floating debris accumulation, the planning is dynamically updated when new accumulation areas emerge. The proposed method is validated with a set of numerical experiments based on a real-world case

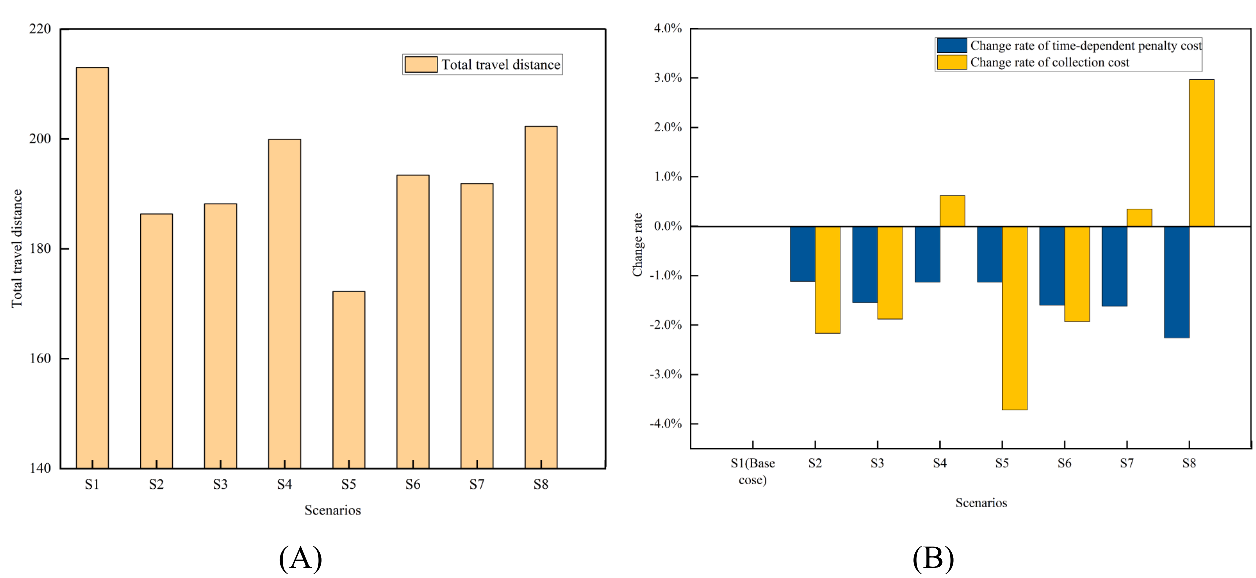

Fig. 9. The impact of changing combinations of unloading points on (A) total travel distance; (B) collection and time-dependent penalty cost.

study at Wushan County in the Three Gorges Reservoir area. Based on the experimental results, three generic managerial implications can be summarized as follows:

1. The time-dependent penalty cost will help drastically improve the collection planning to favor the responsiveness to the accumulation areas with higher priority, e.g., priority classes 1 and 2 in the case, but it may increase the total collection cost. Thus, the level of penalty cost should be properly set up considering the trade-off between cost and service priority.
2. Using different types of collection ships may yield significant impacts on operational planning. For instance, using larger collection ships may help reduce the total collection time and minimize the number of unloading operations, but a higher cost may be incurred. On the other hand, a smaller collection ship with insufficient capacity may further worsen the system's performance. Therefore, choosing the appropriate types of collection ships is important for improving both the cost-effectiveness and operational efficiency of floating debris collection in reservoir areas.
3. The number and locations of the unloading points have a significant impact on the total travel distance, total cost, and responsiveness to accumulation points with higher priority. Increasing the number of unloading points may not lead to a uniform change on all three indicators. Thus, when contracting with the unloading points, the decision-makers may need to consider the balance between cost-effectiveness and responsiveness.
4. The proposed two-stage decision-support framework offers dynamic adjustments and re-routing to the initial predication-based collection plan in response to emerging debris accumulation areas. By effectively inserting these new accumulation areas into existing routes, our experiments indicate a 1.24 % cost saving compared to the single-stage counterpart. Furthermore, there is a reduction of one collection ship needed.

Finally, two suggestions are given for further improvement of the current research. First, taking into account the water level, flow rate as well as other factors, the uncertainty issue should be comprehensively considered, mathematically modeled, and properly treated in the proactive stage with, for example, stochastic or fuzzy approaches (Yu and Solvang, 2020). Second, the performance of the floating debris collection system in the reactive stage needs to be tested in a much more comprehensive fashion with, for instance, Monte Carlo simulation and/or discrete event simulation (Andoh & Yu, 2023).

CRediT authorship contribution statement

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

Data availability

Data will be made available on request.

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Appendix

Tables A1 and A2.

Table A1
Test of parameter values in the GA.

NP	P_m	P_c	Maxgen	Gap	NP	Pm	Pc	Maxgen	Gap	NP	Pm	Pc	Maxgen	Gap
80	**0.9**	**0.1**	**800**	**0.00 %**	50	0.9	0.1	800	1.53 %	100	0.9	0.1	800	0.63 %
80	0.9	0.2	800	0.66 %	50	0.9	0.2	800	1.21 %	100	0.9	0.2	800	0.85 %
80	0.9	0.3	800	1.32 %	50	0.9	0.3	800	0.60 %	100	0.9	0.3	800	0.04 %
80	0.8	0.1	800	0.63 %	50	0.8	0.1	800	1.13 %	100	0.8	0.1	800	1.99 %
80	0.8	0.2	800	2.60 %	50	0.8	0.2	800	0.68 %	100	0.8	0.2	800	1.10 %
80	0.8	0.3	800	0.59 %	50	0.8	0.3	800	0.59 %	100	0.8	0.3	800	0.90 %
80	0.5	0.1	800	1.03 %	50	0.5	0.1	800	4.68 %	100	0.5	0.1	800	0.78 %
80	0.5	0.2	800	0.76 %	50	0.5	0.2	800	1.40 %	100	0.5	0.2	800	0.91 %
80	0.5	0.3	800	0.85 %	50	0.5	0.3	800	0.16 %	100	0.5	0.3	800	0.47 %
80	0.9	0.1	500	0.49 %	50	0.9	0.1	500	2.93 %	100	0.9	0.1	500	2.94 %
80	0.9	0.2	500	1.63 %	50	0.9	0.2	500	0.65 %	100	0.9	0.2	500	1.65 %
80	0.9	0.3	500	0.88 %	50	0.9	0.3	500	0.66 %	100	0.9	0.3	500	1.60 %
80	0.8	0.1	500	4.38 %	50	0.8	0.1	500	4.85 %	100	0.8	0.1	500	1.15 %
80	0.8	0.2	500	0.75 %	50	0.8	0.2	500	0.64 %	100	0.8	0.2	500	2.12 %
80	0.8	0.3	500	0.83 %	50	0.8	0.3	500	1.06 %	100	0.8	0.3	500	0.60 %
80	0.5	0.1	500	2.00 %	50	0.5	0.1	500	4.91 %	100	0.5	0.1	500	0.96 %
80	0.5	0.2	500	3.00 %	50	0.5	0.2	500	4.10 %	100	0.5	0.2	500	2.14 %
80	0.5	0.3	500	0.93 %	50	0.5	0.3	500	1.18 %	100	0.5	0.3	500	2.95 %
80	0.9	0.1	200	1.62 %	50	0.9	0.1	200	3.93 %	100	0.9	0.1	200	4.01 %
80	0.9	0.2	200	4.47 %	50	0.9	0.2	200	5.42 %	100	0.9	0.2	200	1.46 %
80	0.9	0.3	200	1.36 %	50	0.9	0.3	200	1.92 %	100	0.9	0.3	200	1.64 %
80	0.8	0.1	200	7.76 %	50	0.8	0.1	200	7.72 %	100	0.8	0.1	200	4.50 %
80	0.8	0.2	200	3.52 %	50	0.8	0.2	200	2.86 %	100	0.8	0.2	200	6.81 %
80	0.8	0.3	200	3.67 %	50	0.8	0.3	200	0.86 %	100	0.8	0.3	200	2.76 %
80	0.5	0.1	200	3.63 %	50	0.5	0.1	200	6.03 %	100	0.5	0.1	200	7.40 %
80	0.5	0.2	200	1.50 %	50	0.5	0.2	200	3.65 %	100	0.5	0.2	200	4.18 %
80	0.5	0.3	200	2.11 %	50	0.5	0.3	200	5.99 %	100	0.5	0.3	200	3.27 %

Table A2
Test of parameter values in the SAA.

q	T	T_{end}	L	Gap	q	T	Tend	L	Gap	q	T	Tend	L	Gap
0.98	**1000**	**0.00001**	**5**	**0.0000 %**	0.98	1000	0.00001	2	0.2380 %	0.98	1000	0.00001	1	0.0672 %
0.98	200	0.00001	5	0.0426 %	0.98	200	0.00001	2	0.1274 %	0.98	200	0.00001	1	0.1611 %
0.98	500	0.00001	5	0.0300 %	0.98	500	0.00001	2	0.2096 %	0.98	500	0.00001	1	0.0277 %
0.98	1000	0.01	5	0.1284 %	0.98	1000	0.01	2	0.1213 %	0.98	1000	0.01	1	0.3384 %
0.98	200	0.01	5	0.3095 %	0.98	200	0.01	2	0.0282 %	0.98	200	0.01	1	0.2600 %
0.98	500	0.01	5	0.0718 %	0.98	500	0.01	2	0.1780 %	0.98	500	0.01	1	0.3056 %
0.98	1000	1	5	0.2993 %	0.98	1000	1	2	0.0992 %	0.98	1000	1	1	0.3243 %
0.98	200	1	5	0.2129 %	0.98	200	1	2	0.1580 %	0.98	200	1	1	0.3269 %
0.98	500	1	5	0.1141 %	0.98	500	1	2	0.2260 %	0.98	500	1	1	0.2167 %
0.99	1000	0.00001	5	0.1264 %	0.99	1000	0.00001	2	0.1279 %	0.99	1000	0.00001	1	0.3240 %
0.99	200	0.00001	5	0.1577 %	0.99	200	0.00001	2	0.1265 %	0.99	200	0.00001	1	0.4021 %
0.99	500	0.00001	5	0.0812 %	0.99	500	0.00001	2	0.2096 %	0.99	500	0.00001	1	0.1078 %
0.99	1000	0.01	5	0.2629 %	0.99	1000	0.01	2	0.0239 %	0.99	1000	0.01	1	0.1345 %
0.99	200	0.01	5	0.1581 %	0.99	200	0.01	2	0.1673 %	0.99	200	0.01	1	0.0206 %
0.99	500	0.01	5	0.0577 %	0.99	500	0.01	2	0.2993 %	0.99	500	0.01	1	0.1443 %
0.99	1000	1	5	0.2380 %	0.99	1000	1	2	0.0052 %	0.99	1000	1	1	0.2743 %
0.99	200	1	5	0.0491 %	0.99	200	1	2	0.2096 %	0.99	200	1	1	0.1651 %
0.99	500	1	5	0.2129 %	0.99	500	1	2	0.1578 %	0.99	500	1	1	0.3515 %

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